



Analysis of Covariance (ANCOVA)

Some background

ANOVA can be extended to include one or more continuous variables that predict the outcome (or dependent variable). Continuous variables such as these, that are not part of the main experimental manipulation but have an influence on the dependent variable, are known as *covariates* and they can be included in an ANOVA analysis. For example, in the Viagra example from Field (2013), we might expect there to be other things that influence a person's libido other than Viagra. Some possible influences on libido might be the libido of the participant's sexual partner (after all 'it takes two to tango'), other medication that suppresses libido (such as antidepressants), and fatigue. If these variables are measured, then it is possible to control for the influence they have on the dependent variable by including them in the model. What, in effect, happens is that we carry out a hierarchical regression in which our dependent variable is the outcome, and the covariate is entered in the first block. In a second block, our experimental manipulations are entered (in the form of what are called Dummy variables). So, we end up seeing what effect an independent variable has *after* the effect of the covariate. Field (2013) explains the similarity between ANOVA and regression and this is useful reading to understand how ANCOVA works.

The purpose of including covariates in ANOVA is two-fold:

1. *To reduce within-group error variance*: In ANOVA we assess the effect of an experiment by comparing the amount of variability in the data that the experiment can explain, against the variability that it cannot explain. If we can explain some of this 'unexplained' variance (SS_R) in terms of covariates, then we reduce the error variance, allowing us to more accurately assess the effect of the experimental manipulation (SS_M).
2. *Elimination of Confounds*: In any experiment, there may be unmeasured variables that confound the results (i.e. a variable that varies systematically with the experimental manipulation). If any variables are known to influence the dependent variable being measured, then ANCOVA is ideally suited to remove the bias of these variables. Once a possible confounding variable has been identified, it can be measured and entered into the analysis as a covariate.

The Example

Imagine that the researcher who conducted the Viagra study in Field (2013) suddenly realized that the libido of the participants' sexual partners would effect that participant's own libido (especially because the measure of libido was behavioural). Therefore, the researcher repeated the study on a different set of participants, but took a measure of the partner's libido. The partner's libido was measured in terms of how often they tried to initiate sexual contact.

Assumptions in ANCOVA

ANCOVA has the same assumptions as any linear model (see your handout on bias) except that there are two important additional considerations: (1) independence of the covariate and treatment effect, and (2) homogeneity of regression slopes. The first one basically means that the covariate should not be different across the groups in the analysis (in other words, if you did an ANOVA or *t*-test using the groups as the independent variable and the covariate as the outcome, this analysis should be non-significant). This assumption is quite involved so all I'll say is read my book chapter for more information, or read Miller and Chapman (2001).

When an ANCOVA is conducted we look at the overall relationship between the outcome (dependent variable) and the covariate: we fit a regression line to the entire data set, ignoring to which group a person belongs. In fitting this overall model we, therefore, assume that this overall relationship is true for all groups of participants. For example, if there's a positive relationship between the covariate and the outcome in one group, we assume that there is a positive relationship in all of the other groups too. If, however, the relationship between the outcome (dependent variable) and covariate differs across the groups then the overall regression model is inaccurate (it does not represent all of the groups). This assumption is very important and is called the assumption of **homogeneity of regression slopes**. The best way to think of this assumption is to imagine plotting a scatterplot for each experimental condition with the covariate



on one axis and the outcome on the other. If you then calculated, and drew, the regression line for each of these scatterplots you should find that the regression lines look more or less the same (i.e. the values of b in each group should be equal).

Figure 1 shows scatterplots that display the relationship between partner's libido (the covariate) and the outcome (participant's libido) for each of the three experimental conditions (different colours and symbols). Each symbol represents the data from a particular participant, and the type of symbol tells us the group (circles = placebo, triangles = low dose, squares = high dose). The lines are the regression slopes for the particular group, they summarise the relationship between libido and partner's libido shown by the dots (blue = placebo group, green = low-dose group, red = high-dose group). It should be clear that there is a positive relationship (the regression line slopes upwards from left to right) between partner's libido and participant's libido in both the placebo and low-dose conditions. In fact, the slopes of the lines for these two groups (blue and green) are very similar, showing that the relationship between libido and partner's libido is very similar in these two groups. This situation is an example of homogeneity of regression slopes (the regression slopes in the two groups are similar). However, in the high-dose condition there appears to be no relationship at all between participant's libido and that of their partner (the squares are fairly randomly scattered and the regression line is very flat and shows a slightly negative relationship). The slope of this line is very different to the other two, and this difference gives us cause to doubt whether there is homogeneity of regression slopes (because the relationship between participant's libido and that of their partner is different in the high-dose group to the other two groups). We'll have a look how to test this assumption later.

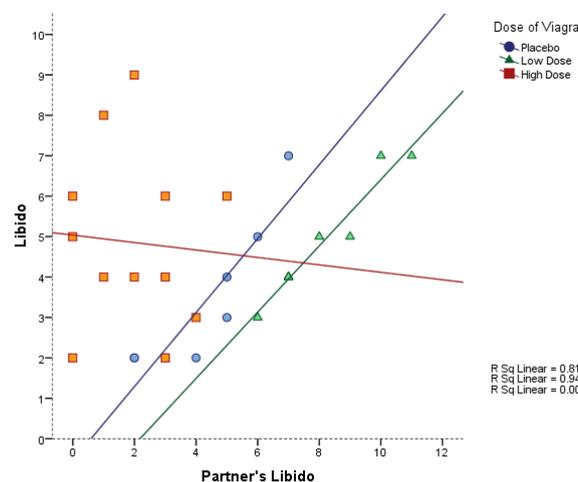


Figure 1: Scatterplot of Libido against Partner's libido for each of the experimental conditions

ANCOVA on SPSS

Entering Data

The data for this example are in Table 1, which shows the participant's libido and their partner's libido. The mean libido (and SD in brackets) of the participants' libido scores are in Table 2. In essence, the data should be laid out in the Data Editor as they are Table 1. Without the covariate, the design is simply a one-way independent design, so we would enter these data using a coding variable for the independent variable, and scores on the dependent variable will go in a different column. All that changes is that we have an extra column for the covariate scores.



- Covariates are entered into the SPSS data editor in a new column (each covariate should have its own column).
- Covariates can be added to any of the different ANOVAs we have covered on this course!
 - When a covariate is added the analysis is called analysis of covariance (so, for example, you could have a two-way repeated measures Analysis of Covariance, or a three way mixed ANCOVA).



Table 1: Data from ViagraCov.sav

Dose	Participant's Libido	Partner's Libido
Placebo	3	4
	2	1
	5	5
	2	1
	2	2
	2	2
	7	7
	2	4
	4	5
Low Dose	7	5
	5	3
	3	1
	4	2
	4	2
	7	6
	5	4
	4	2
High Dose	9	1
	2	3
	6	5
	3	4
	4	3
	4	3
	4	2
	6	0
	4	1
	6	3
	2	0
	8	1
	5	0

So, create a coding variable called **dose** and use the *Labels* option to define value labels (e.g. 1 = placebo, 2 = low dose, 3 = high dose). There were nine participants in the placebo condition, so you need to enter 9 values of 1 into this column (so that the first 9 rows contain the value 1), followed by eight values of 2 to represent the people in the low dose group, and followed by thirteen values of 3 to represent the people in the high dose group. At this point, you should have one column with 30 rows of data entered. Next, create a second variable called **libido** and enter the 30 scores that correspond to the participant's libido. Finally, create a third variable called **partner**, use the *Labels* option to give this variable a more descriptive title of 'partner's libido'. Then, enter the 30 scores that correspond to the partner's libido.

Table 2: Means (and standard deviations) from ViagraCovariate.sav

Dose	Participant's Libido	Partner's Libido
Placebo	3.22 (1.79)	3.44 (2.07)
Low Dose	4.88 (1.46)	3.12 (1.73)
High Dose	4.85 (2.12)	2.00 (1.63)

Main Analysis

Most of the *General Linear Model* (GLM) procedures in SPSS contain the facility to include one or more covariates. For designs that don't involve repeated measures it is easiest to conduct ANCOVA via the GLM *Univariate* procedure. To

access the main dialog box select **Analyze** **General Linear Model** **Univariate...** (see Figure 2). The main dialog box is similar to that for one-way ANOVA, except that there is a space to specify covariates. Select **Libido** and drag this variable to the box labelled *Dependent Variable* or click on . Select **Dose** and drag it to the box labelled *Fixed Factor(s)* and then select **Partner_Libido** and drag it to the box labelled *Covariate(s)*.

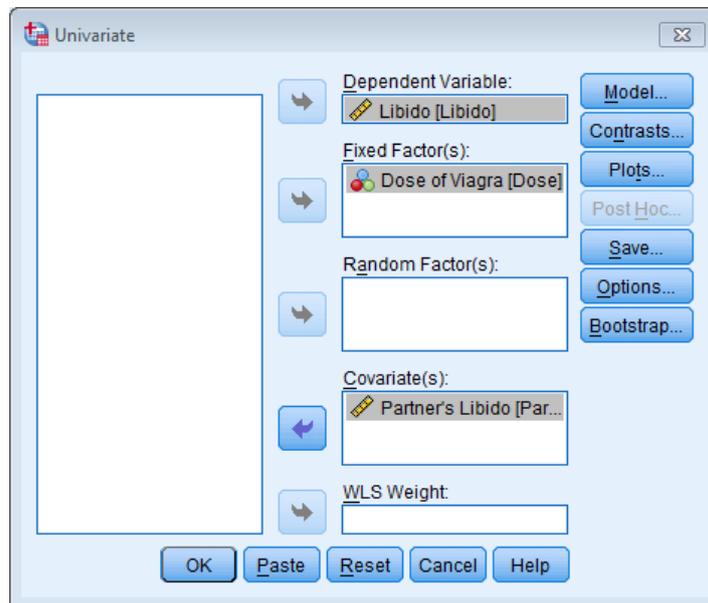


Figure 2: Main dialog box for GLM univariate

Contrasts and Other Options

There are various dialog boxes that can be accessed from the main dialog box. The first thing to notice is that if a covariate is selected, the post hoc tests are disabled (you cannot access this dialog box). Post hoc tests are not designed for situations in which a covariate is specified, however, some comparisons can still be done using contrasts.

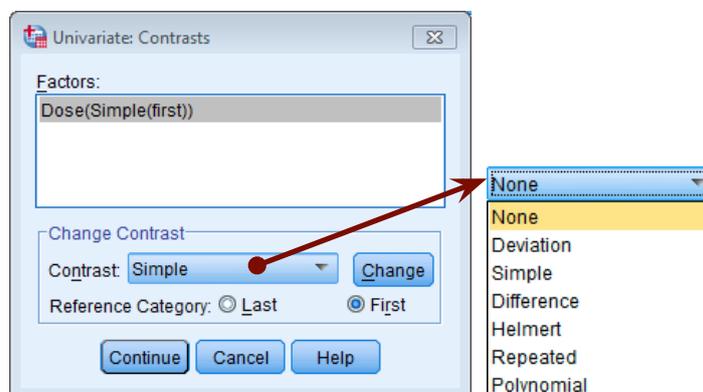


Figure 3: Options for standard contrasts in GLM univariate

Click on **Contrasts...** to access the *contrasts* dialog box. This dialog box is different to the one we met for ANOVA in that you cannot enter codes to specify particular contrasts. Instead, you can specify one of several standard contrasts. These standard contrasts were listed in my book. In this example, there was a placebo control condition (coded as the first group), so a sensible set of contrasts would be simple contrasts comparing each experimental group with the control. To select a type of contrast click on **None** to access a drop-down list of possible contrasts. Select a type of contrast (in this case *Simple*) from this list and the list will automatically disappear. For simple contrasts you have the option of specifying a reference category (which is the category against which all other groups are compared). By default the reference category is the last category: because in this case the control group was the first category (assuming that you coded placebo as 1) we need to change this option by selecting **First**. When you have selected a new contrast

option, you must click on **Change** to register this change. The final dialog box should look like Figure 3. Click on **Continue** to return to the main dialog box.

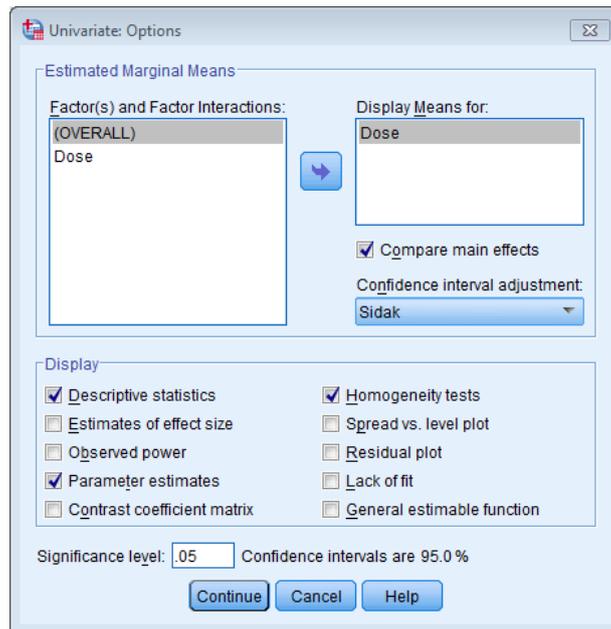
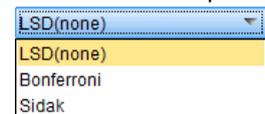


Figure 4: *Options* dialog box for GLM univariate

Another way to get *post hoc* tests is by clicking on **Options...** to access the *options* dialog box (see Figure 4). To specify *post hoc* tests, select the independent variable (in this case **Dose**) from the box labelled *Estimated Marginal Means: Factor(s) and Factor Interactions* and drag it to the box labelled *Display Means for* or click on **→**. Once a variable has been transferred, the box labelled *Compare main effects* becomes active and you should select this option (**Compare main effects**). If this option is selected, the box labelled *Confidence interval adjustment* becomes active and you can click on **LSD(none)** to see a choice of three adjustment levels. The default is to have no adjustment and simply perform a Tukey LSD *post hoc* test (this option is not recommended); the second is to ask for a Bonferroni correction (recommended); the final option is to have a **Sidak correction**. The Sidak correction is similar to the Bonferroni correction but is less conservative and so should be selected if you are concerned about the loss of power associated with Bonferroni corrected values. For this example use the Sidak correction (we will use Bonferroni later in the book). As well as producing *post hoc* tests for the **Dose** variable, placing **dose** in the *Display Means for* box will create a table of estimated marginal means for this variable. These means provide an estimate of the *adjusted* group means (i.e. the means adjusted for the effect of the covariate). When you have selected the options required, click on **Continue** to return to the main dialog box.



As with one-way ANOVA, the main dialog box has a **Bootstrap...** button. Selecting this option will bootstrap confidence intervals around the estimated marginal means, parameter estimates and *post hoc* tests, but not the main *F* test. This can be useful so select the options in Figure 5. Click on **OK** in the main dialog box to run the analysis.

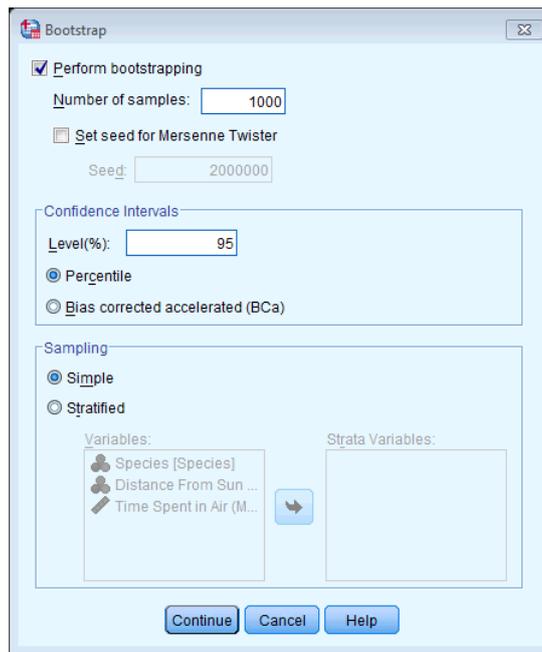


Figure 5: *Bootstrap* dialog box

Output from ANCOVA

Main Analysis

Output 1 shows (for illustrative purposes) the ANOVA table for these data when the covariate is not included. It is clear from the significance value that there are no differences in libido between the three groups, therefore Viagra seems to have no significant effect on libido.

Tests of Between-Subjects Effects

Dependent Variable: Libido

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	16.844 ^a	2	8.422	2.416	.108
Intercept	535.184	1	535.184	153.522	.000
Dose	16.844	2	8.422	2.416	.108
Error	94.123	27	3.486		
Total	683.000	30			
Corrected Total	110.967	29			

a. R Squared = .152 (Adjusted R Squared = .089)

Output 1

Output 2 shows the results of Levene's test when partner's libido is included in the model as a covariate. Levene's test is significant, indicating that the group variances are not equal (hence the assumption of homogeneity of variance is likely been violated). However, Levene's test is not necessarily the best way to judge whether variances are unequal enough to cause problems (see your handout from week 2 or Field, 2013 chapter 5). We saw in week 2 that a good double check is to look at the variance ratio¹. The variance ratio for these data is $4.49/2.13 = 2.11$. This value is greater than 2 indicating that our variances are probably heterogeneous! We saw last term that we could try to transform our data to correct this problem (have a go if you're feeling keen), but for the time being don't worry too much about the differences in variances.

¹ Reminder 1: the variance ratio is the largest variance divided by the smallest and should be less than about 2. You can get these variances by squaring the SDs in Table 1.



Levene's Test of Equality of Error Variances^a

Dependent Variable: Libido

F	df1	df2	Sig.
4.618	2	27	.019

Tests the null hypothesis that the error variance of the dependent variable is equal across groups.

a. Design: Intercept + Partner_Libido + Dose

Output 2

Output 3 shows the ANOVA table with the covariate included. Compare this to the summary table when the covariate was not included. The format of the ANOVA table is largely the same as without the covariate, except that there is an additional row of information about the covariate (**partner**). Looking first at the significance values, it is clear that the covariate significantly predicts the dependent variable, because the significance value is less than .05. Therefore, the person's libido is influenced by their partner's libido. What's more interesting is that when the effect of partner's libido is removed, the effect of Viagra becomes significant (p is .027 which is less than .05). The amount of variation accounted for by the model (SS_M) has increased to 31.92 units (corrected model) of which Viagra accounts for 25.19 units. Most important, the large amount of variation in libido that is accounted for by the covariate has meant that the unexplained variance (SS_R) has been reduced to 79.05 units. Notice that SS_T has not changed; all that has changed is how that total variation is explained.

This example illustrates how ANCOVA can help us to exert stricter experimental control by taking account of confounding variables to give us a 'purer' measure of effect of the experimental manipulation. Without taking account of the libido of the participants' partners we would have concluded that Viagra had no effect on libido, yet clearly it does. Looking back at the group means from Table 1:e 1 it seems pretty clear that the significant ANOVA reflects a difference between the placebo group and the two experimental groups (because the low and high dose group have very similar means whereas the placebo group have a lower mean). However, we need to check the contrasts to verify this conclusion.

Tests of Between-Subjects Effects

Dependent Variable: Libido

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	31.920 ^a	3	10.640	3.500	.030
Intercept	76.069	1	76.069	25.020	.000
Partner_Libido	15.076	1	15.076	4.959	.035
Dose	25.185	2	12.593	4.142	.027
Error	79.047	26	3.040		
Total	683.000	30			
Corrected Total	110.967	29			

a. R Squared = .288 (Adjusted R Squared = .205)

Output 3



We can report the main effect of Dose in APA format as:

- ✓ There was a significant effect of Viagra on levels of libido after controlling for the effect of partner's libido, $F(2, 26) = 4.14, p = .027$.

Contrasts

Output 4 shows the result of the contrast analysis specified in Figure 3 and compares level 2 (low dose) against level 1 (placebo) as a first comparison, and level 3 (high dose) against level 1 (placebo) as a second comparison. These contrasts are consistent with what was specified: all groups are compared to the first group. The group differences are displayed: a difference value, standard error, significance value and 95% confidence interval. These results show that both the low-dose group (contrast 1, $p = .045$) and high-dose group (contrast 2, $p = .010$) had significantly different libidos than the placebo group.

These contrasts tell us that there were group differences, but to interpret them we need to know the means. We produced the means in Table 2 so surely we can just look at these values? Actually we can't because these group means have not been adjusted for the effect of the covariate. These original means tell us nothing about the group differences reflected by the significant ANCOVA. Output 5 gives the adjusted values of the group means and it is these values that



should be used for interpretation (this is the main reason for selecting the *Display Means for* option). From these adjusted means you can see that libido increased across the three doses.

Contrast Results (K Matrix)

		Dependent Variable
		Libido
Dose of Viagra Simple Contrast^a		
Level 2 vs. Level 1	Contrast Estimate	1.786
	Hypothesized Value	0
	Difference (Estimate - Hypothesized)	1.786
	Std. Error	.849
	Sig.	.045
	95% Confidence Interval for Difference	Lower Bound Upper Bound
Level 3 vs. Level 1	Contrast Estimate	2.225
	Hypothesized Value	0
	Difference (Estimate - Hypothesized)	2.225
	Std. Error	.803
	Sig.	.010
	95% Confidence Interval for Difference	Lower Bound Upper Bound

a. Reference category = 1

Output 4

Estimates

Dependent Variable: Libido

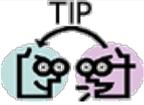
Dose of Viagra	Mean	Std. Error	95% Confidence Interval		Bootstrap for Mean ^{gn}			
			Lower Bound	Upper Bound	Bias	Std. Error	BCa 95% Confidence Interval	
							Lower	Upper
Placebo	2.926 ^a	.596	1.701	4.152	.030	.446	2.111	4.125
Low Dose	4.712 ^a	.621	3.436	5.988	.033 ^{go}	.392 ^{go}	3.988 ^{go}	5.620 ^{go}
High Dose	5.151 ^a	.503	4.118	6.184	.041	.651	3.923	6.771

a. Covariates appearing in the model are evaluated at the following values: Partner's Libido = 2.73.

gn. Unless otherwise noted, bootstrap results are based on 1000 bootstrap samples

go. Based on 999 samples

Output 5



TIP

We can report these contrasts in APA format as:

- ✓ Planned contrasts revealed that having a high, $p = .010$, 95% CI [0.58, 3.88], and low, $p = .045$, 95% CI [0.04, 3.53], dose of Viagra significantly increased libido compared to having a placebo.

Post Hoc Tests

Output 6 shows the results of the Sidak corrected *post hoc* comparisons that were requested as part of the *options* dialog box. The bottom table shows the bootstrapped significance and confidence intervals for these tests and because these will be robust we'll interpret this table (again, remember, your values will differ because of how bootstrapping works). There is a significant difference between the placebo group and both the low ($p = .003$) and high ($p = .021$) dose groups. The high and low-dose groups did not significantly differ ($p = .56$). It is interesting that the significant difference between the low-dose and placebo groups when bootstrapped ($p = .003$) is not present for the normal *post hoc* tests ($p = .130$). This could reflect properties of the data that have biased the non-robust version of the *post hoc* test.

Interpreting the Covariate

One way to discover the effect of the covariate is simply to draw a scatterplot of the covariate against the outcome. The resulting scatterplot for these data shows that the effect of covariate is that as partner's libido increases, so does the participant's libido (as shown by the slope of the regression line).



TIP

We can report the effect of the covariate in APA format as:

- ✓ The covariate, partner's libido, was significantly related to the participant's libido, $F(1, 26) = 4.96, p = .035$.



Pairwise Comparisons

Dependent Variable: Libido

(I) Dose of Viagra	(J) Dose of Viagra	Mean Difference (I-J)	Std. Error	Sig. ^b	95% Confidence Interval for Difference ^b	
					Lower Bound	Upper Bound
Placebo	Low Dose	-1.786	.849	.130	-3.953	.381
	High Dose	-2.225 [*]	.803	.030	-4.273	-.177
Low Dose	Placebo	1.786	.849	.130	-.381	3.953
	High Dose	-.439	.811	.932	-2.509	1.631
High Dose	Placebo	2.225 [*]	.803	.030	.177	4.273
	Low Dose	.439	.811	.932	-1.631	2.509

Based on estimated marginal means

*. The mean difference is significant at the

b. Adjustment for multiple comparisons: Sidak.

Bootstrap for Pairwise Comparisons

Dependent Variable: Libido

(I) Dose of Viagra	(J) Dose of Viagra	Mean Difference (I-J)	Bootstrap ^a				
			Bias	Std. Error	Sig. (2-tailed)	BCa 95% Confidence Interval	
				Lower	Upper		
Placebo	Low Dose	-1.786	-.003 ^b	.535 ^b	.003 ^b	-2.778 ^b	-.765 ^b
	High Dose	-2.225	-.011	.760	.021	-3.752	-.832
Low Dose	Placebo	1.786	.003 ^b	.535 ^b	.003 ^b	.663 ^b	2.879 ^b
	High Dose	-.439	-.008 ^b	.745 ^b	.558 ^b	-1.937 ^b	.935 ^b
High Dose	Placebo	2.225	.011	.760	.021	.686	3.923
	Low Dose	.439	.008 ^b	.745 ^b	.558 ^b	-.938 ^b	1.945 ^b

a. Unless otherwise noted, bootstrap results are based on 1000 bootstrap samples

b. Based on 999 samples

Output 6

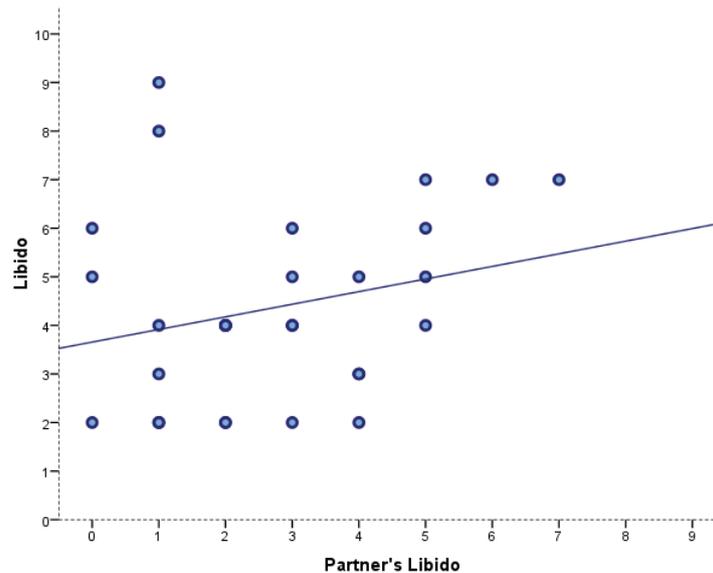


Figure 6: Scatterplot of participants' libido scores against those of their partner

Testing the Assumption of Homogeneity of Regression Slopes

To test the assumption of homogeneity of regression slopes we need to rerun the ANCOVA but this time use a customized model. Access the main dialog box as before and place the variables in the same boxes as before (so the finished box should look like Figure 2). To customize the model we need to access the model dialog box by clicking on [Model...](#). To customize your model, select [Custom](#) to activate the dialog box (Figure 7). The variables specified in the main dialog box are listed on the left-hand side. To test the assumption of homogeneity of regression slopes, we need



to specify a model that includes the interaction between the covariate and independent variable. Hence, to begin with you should select **Dose** and **Partner_Libido** (you can select both of them at the same time by holding down *Ctrl*). Then, click on the drop-down menu and change it to **Main effects**. Having selected this, click on to move the main effects of **Dose** and **Partner_Libido** to the box labelled *Model*. Next we need to specify the interaction term. To do this, select **Dose** and **Partner_Libido** simultaneously (by holding down the *Ctrl* key while you click on the two variables), then select **Interaction** in the drop-down list and click on . This action moves the interaction of **Dose** and **Partner_Libido** to the box labelled *Model*. The finished dialog box should look like Figure 7. Having specified our two main effects and the interaction term, click on **Continue** to return to the main dialog box and then click on **OK** to run the analysis.

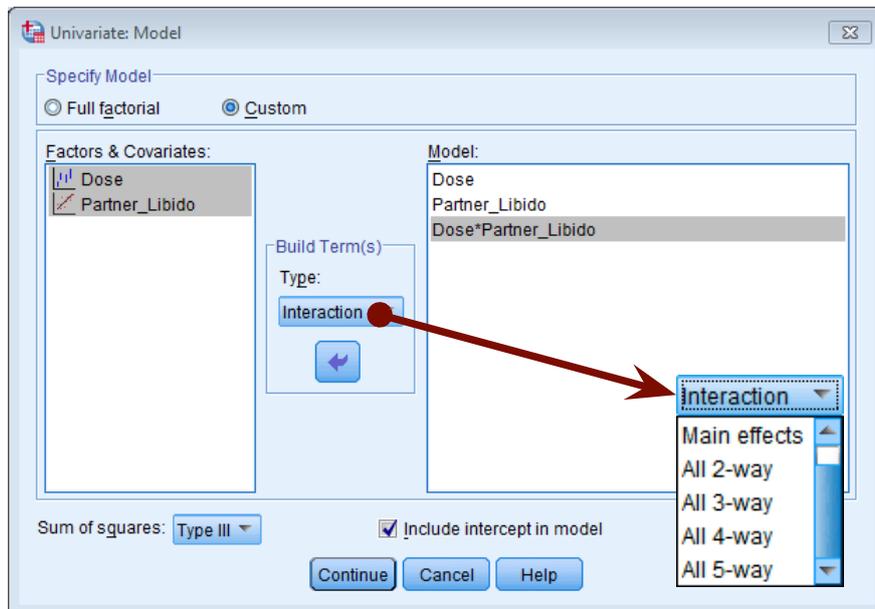


Figure 7: GLM univariate *model* dialog box

SPSS Output 6 shows the main summary table for the ANCOVA using only the interaction term. Look at the significance value of the covariate by dependent variable interaction (**dose*partner**), if this effect is significant then the assumption of homogeneity of regression slopes has been broken. The effect here is significant ($p = .028$); therefore the assumption is not tenable. Although this finding is not surprising given the pattern of relationships shown in Figure 1 it does raise concern about the main analysis. This example illustrates why it is important to test assumptions and not to just blindly accept the results of an analysis.

Tests of Between-Subjects Effects

Dependent Variable: Libido

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	52.346 ^a	5	10.469	4.286	.006
Intercept	53.542	1	53.542	21.921	.000
Dose	36.558	2	18.279	7.484	.003
Partner_Libido	17.182	1	17.182	7.035	.014
Dose * Partner_Libido	20.427	2	10.213	4.181	.028
Error	58.621	24	2.443		
Total	683.000	30			
Corrected Total	110.967	29			

a. R Squared = .472 (Adjusted R Squared = .362)

Output 7

Guided Example

A few years back I was stalked. You'd think they could have found someone a bit more interesting to stalk, but apparently times were hard. It could have been a lot worse than it was, but it wasn't particularly pleasant. I imagined a world in

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which a psychologist tried two different therapies on different groups of stalkers (25 stalkers in each group—this variable is called **Group**). To the first group of stalkers he gave what he termed cruel-to-be-kind therapy (every time the stalkers followed him around, or sent him a letter, the psychologist attacked them with a cattle prod). The second therapy was psychodysshamic therapy, in which stalkers were hypnotised and regressed into their childhood to discuss their penis (or lack of penis), their father’s penis, their dog’s penis, the seventh penis of a seventh penis and any other penis that sprang to mind. The psychologist measured the number of hours in the week that the stalker spent stalking their prey both before (**stalk1**) and after (**stalk2**) treatment. Analyse the effect of therapy on stalking behaviour after therapy, covarying for the amount of stalking behaviour before therapy.

Cruel to be Kind Therapy		Psychodysshamic Therapy	
Initial Stalking	Stalking After Therapy	Initial Stalking	Stalking After Therapy
47	11	52	47
50	18	53	47
51	34	54	50
52	40	57	55
53	50	58	56
57	54	60	56
57	55	61	61
60	58	61	61
63	59	62	61
66	60	65	61
68	61	66	62
72	61	66	62
72	62	66	62
73	63	71	64
75	64	71	64
77	65	72	64
79	65	75	70
85	78	77	74
62	55	80	78
71	63	87	78
53	52	75	62
64	80	57	71
79	35	59	55
75	70	46	46
60	61	89	79



- Enter the data into SPSS. (Hint: The data should not be entered as they are in the table above).
- Save the data onto a disk in a file called **stalker.sav**.



→ Conduct the appropriate analysis to see whether the two therapies had a significant effect on stalking behaviour when controlling for the person's general tendency to stalk.

What is/are the independent variable(s) and how many levels do they have?

Your Answer:

What is the dependent variable?

Your Answer:

What is the covariate?

Your Answer:

What analysis have you performed?

Your Answer:

Has the assumption of homogeneity of variance been met? (Quote relevant statistics in APA format).

Your Answer:

Report the effect of 'therapy' in APA format. Is this effect significant and how would you interpret it?

Your Answer:



Report the effect of 'initial stalking' in APA format. Is this effect significant and how would you interpret it?

Your Answer:

Some answers to this question can be found on the companion website of my book.

Unguided Example

A marketing manager was interested in the therapeutic benefit of certain soft drinks for curing hangovers. He took 15 people out on the town one night and got them drunk. The next morning as they awoke, dehydrated and feeling as though they'd licked a camel's sandy feet clean with their tongue, he gave five of them water to drink, five of them Lucozade (a very nice glucose-based UK drink) and the remaining five a leading brand of cola (this variable is called **drink**). He measured how well they felt (on a scale from 0 = I feel like death to 10 = I feel really full of beans and healthy) two hours later (this variable is called **well**). He measured how **drunk** the person got the night before on a scale of 0 = as sober as a nun to 10 = flapping about like a haddock out of water on the floor in a puddle of their own vomit.

Water		Lucozade		Cola	
Well	Drunk	Well	Drunk	Well	Drunk
5	5	5	6	5	2
5	3	4	6	6	3
6	2	6	4	6	2
6	1	8	2	6	3
3	7	6	3	6	2



- Enter the data into SPSS. (Hint: The data should not be entered as they are in the table above).
- Save the data onto a disk in a file called **HangoverCure.sav**.

→ Conduct the appropriate analysis to see whether the drinks differ in their ability to control hangovers when controlling for how much was drunk the night before.

Some answers to this question can be found on the companion website of my book.

Multiple Choice Questions



Complete the multiple choice questions for **Chapter 12** on the companion website to Field (2013): <https://studysites.uk.sagepub.com/field4e/study/mcqs.htm>. If you get any wrong, re-read this handout (or Field, 2013, Chapter 12) and do them again until you get them all correct.

References

Field, A. P. (2013). *Discovering statistics using IBM SPSS Statistics: And sex and drugs and rock 'n' roll* (4th ed.). London: Sage.

Miller, G. A., & Chapman, J. P. (2001). Misunderstanding analysis of covariance. *Journal of Abnormal Psychology*, 110(1), 40-48. doi: Doi 10.1037//0021-843x.110.1.40

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