

## PSY 345 -- Analyses of the Ajax Survey Data

### 1. Reporting Estimates of Population Parameters and Their Accuracy

#### 1.1 Means

Example: What is the mean rating of job satisfaction? [e4 to e7]

compute jobsat=mean(e4 to e7).

#### **Mean and Standard Deviation and Confidence Interval**

Point and Click: Analyze → Descriptive Statistics → Explore. Specify *jobsat* on the Dependent List. Specify Display Statistics Only, and click on Statistics and confirm that Descriptives is checked, with the appropriate confidence interval specified.

Syntax: examine jobsat /plot=none.

**Case Processing Summary**

	Cases					
	Valid		Missing		Total	
	N	Percent	N	Percent	N	Percent
JOBSAT	924	99.5%	5	.5%	929	100.0%

**Descriptives**

			Statistic	Std. Error
JOBSAT	Mean		2.8472	.01852
	95% Confidence Interval for Mean	Lower Bound	2.8109	
		Upper Bound	2.8836	
	5% Trimmed Mean		2.8592	
	Median		3.0000	
	Variance		.317	
	Std. Deviation		.56281	
	Minimum		1.00	
	Maximum		4.00	
	Range		3.00	
	Interquartile Range		.5000	
	Skewness		-.355	.080
	Kurtosis		.865	.161

The **standard error of the mean** is equal to the sample standard deviation divided by the square root of the sample size:  $.56281/\sqrt{924} = .01852$ . Interpretation: If we took a large number of samples of this size from this population and calculated the mean each time, the SD of the distribution of means would be equal to .01852.

The **confidence interval of the mean** is a measure of the accuracy of the estimate of the population mean. It is equal to the mean +/- the standard error of the mean multiplied by the *z*- or *t*-value associated with the size of the CI. For the 95% interval, we use *z* for .05/2, which is 1.96, so the CI is 2.8472 +/- .01852 \* 1.96, which equals the values given in the table. Interpretation: If we took 100 samples of this size from the population and calculated the 95% confidence interval each time, on 95 of those times, the confidence interval would contain the population mean. Strictly speaking, it is not correct to say that we are 95% confident that the population mean falls within a particular CI, although this a common usage. When someone makes this sort of statement, translate the '95% confident' part to mean that the probability is .95 that a CI calculated in the above way will contain the population mean. In other words, the probability doesn't refer to a particular interval once calculated, but to a set of CIs calculated from a number of samples of the specified size.

Report: The mean rating on the job satisfaction items was 2.85 (95% CI 2.81-2.88).

## 1.2 Proportions

Example: What proportion of employees reported that they had experienced bullying, intimidation, or unfair treatment by a supervisor or manager in the past 12 months? (L4).

### **One-way Frequency Distribution and Confidence Interval**

Point-and click: Analyze → Descriptive Statistics → Frequencies. Specify L4.

Syntax: freq L4.

**L4 bullying by supervisor**

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1 yes	181	19.5	19.6	19.6
	2 no	742	79.9	80.4	100.0
	Total	923	99.4	100.0	
Missing	System	6	.6		
Total		929	100.0		

The standard error of a proportion is  $\sqrt{(pq/N)}$ , where *p* is the proportion of one category, and *q* = 1 - *p*. So, the 95% CI for this proportion is .196 +/-  $\sqrt{.196*(1-.196)/923}$  \* 1.96 = .196 +/- .026, (.170 - .222). This CI of a proportion has the same kind of interpretation as that for the mean.

Report: The proportion of employees who had experienced bullying, etc by a supervisor or manager was .196 (95% CI .17 - .22). We could also report a percentage: 19.6% (95% CI 17.0% - 22.2%).

## 2. Comparing Sample Estimates to Fixed Values

### 2.1 Means

Example: Is the mean rating of *jobsat* significantly higher than the mid-point of the scale?

#### **The One-Sample *t*-Test**

Point-and-click: Analyze → Compare Means → One-Sample T Test. Specify *jobsat*. Specify 2.5 as the Test Value.

Syntax: `t-test testval=2.5/vars=jobsat.`

**One-Sample Statistics**

	N	Mean	Std. Deviation	Std. Error Mean
JOBSAT	924	2.8472	.56281	.01852

**One-Sample Test**

	Test Value = 2.5					
	t	df	Sig. (2-tailed)	Mean Difference	95% Confidence Interval of the Difference	
					Lower	Upper
JOBSAT	18.754	923	.000	.3472	.3109	.3836

Report: The mean of *jobsat* (2.85, sd .56) for the sample was significantly higher than the specified value of 2.5,  $t(923) = 18.75, p < .0005$ .

### 2.2 Proportions

Example: Is the proportion of employees who had experienced bullying, etc, by a supervisor or manager significantly different from an (imaginary) Workplace Guideline of 20%?

#### **The One-Sample Chi-Squared Test**

Point-and-click: Analyze → Nonparametric Tests → Chi-Square. Specify *L4* in the Test Variable List. Click on Values in the Expected Values box, and then Add the expected proportions, starting with that for the lowest-numbered category, i.e., .20 then .80.

Syntax: `npar tests chisquare=L4/expected=.2 .8.`

**L4 bullying by supervisor**

	Observed N	Expected N	Residual
1 yes	181	184.6	-3.6
2 no	742	738.4	3.6
Total	923		

**Test Statistics**

	L4 bullying by supervisor
Chi-Square <sup>a</sup>	.088
df	1
Asymp. Sig.	.767

a. 0 cells (.0%) have expected frequencies less than 5. The minimum expected cell frequency is 184.6.

Report : There was no significant difference between the proportion in the sample  $[181/(181 + 742) = .1961]$  and the fixed value of .20,  $\chi^2(1; N=923) = .088, p = .767$ . We therefore have no reason to think that the proportion in the population is different from 20%<sup>1</sup>.

### **3. Reporting Differences Between Estimates of Population Parameters and Their Significance**

#### 3.1 Differences Between Two Means

##### 3.1.1 Independent Groups

Example: Is there a significant difference between the *jobsat* ratings of those who reported experiencing bullying, etc, by a supervisor or manager, and those who did not?

#### **Independent Groups *t*-test**

Point-and-click: Analyze → Compare Means → Independent-Samples T Test. Specify *jobsat* as the Test Variable. Specify L4 as the Grouping Variable. Click on Define Groups and enter 1 and 2 as the codes for the two groups.

Syntax: *t*-test groups=L4(1,2)/vars=*jobsat*.

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<sup>1</sup> Note that reaching this conclusion is not the same thing as 'proving' that the proportion in the population isn't different from 20%. If we calculate (say) a 99% CI for this sample, we find that it ranges from .16 to .23, which contains values which are clearly different from .20. Therefore the sample could have come from a population in which fewer (or more) than 20% of employees had experienced bullying, etc, by a supervisor or manager.

**Group Statistics**

		N	Mean	Std. Deviation	Std. Error Mean
JOBSAT	1 yes	181	2.4931	.64913	.04825
	2 no	738	2.9347	.50455	.01857

Note: The original *t*-test output table was broken into the two following pieces to fit on the page.

**Independent Samples Test**

		Levene's Test for Equality of Variances		t-test for Equality of Means		
		F	Sig.	t	df	Sig. (2-tailed)
JOBSAT	Equal variances assumed	18.053	.000	-9.933	917	.000
	Equal variances not assumed			-8.542	236.030	.000

**Independent Samples Test**

		t-test for Equality of Means			
		Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
				Lower	Upper
JOBSAT	Equal variances assumed	-.4416	.04446	-.52889	-.35438
	Equal variances not assumed	-.4416	.05170	-.54349	-.33979

The Levene test for the equality of variances is significant [ $F(1, 917) = 18.05, p < .0005$ ], so we use the *t*-test results in which equal variances are not assumed<sup>2</sup>.

Report: There was a significant difference between the mean *jobsat* ratings of those who had experienced bullying, etc by a supervisor or manager and those who had not,

<sup>2</sup> For the unequal variance case, SPSS calculates adjusted (more conservative) degrees of freedom for the *t*-test, using a method due to Satterthwaite. The formula for the adjusted *df* is  $(s_1^2/n_1 + s_2^2/n_2)^2 / [(s_1^2/n_1)^2/(n_1 - 1) + (s_2^2/n_2)^2/(n_2 - 1)]$  where  $s_1$  and  $s_2$  are the sample standard deviations and  $n_1$  and  $n_2$  are the numbers in each group. The greater the difference between the standard deviations and/or the number of cases in each group, the smaller the adjusted *df* will be, compared to the unadjusted *df*. In this case the calculation is  $(.64913^2/181 + .50455^2/738)^2 / [(.64913^2/181)^2/180 + (.50455^2/738)^2/737] = 236.03$ .

$t(236.03) = 8.54, p < .0005$ . The mean for employees who had experienced bullying (2.49, sd .65) was lower than for those who had not (2.93, sd .50).

Note: The standard error of the difference between the means is equal to the square root of the sum of the squared standard errors of the means of the two groups, i.e.,  $\sqrt{(.04825^2 + .01857^2)} = .0517$ , and this figure is what SPSS gives for the 'unequal variances assumed' result. When the standard deviations of the two groups can be assumed to be the same, it is usual to pool the standard deviations of the two groups, and to base the standard error of the difference on that. The pooled within-group standard deviation (it is called this to distinguish it from a standard deviation which includes between- as well as within-groups variation) is equal to  $\sqrt{[sd_1^2 * (n_1 - 1) + sd_2^2 * (n_2 - 1)] / (n_1 + n_2 - 2)}$ ; so, in this case,  $SD = \sqrt{\{[(.50455^2 * 738 - 1) + .64913^2 * 181 - 1] / (738 + 181 - 2)\}} = .53601$ . This figure can then be used in the calculation of the standard error of the difference:  $\sqrt{(.53601^2 / 181 + .53601^2 / 738)} = .04446$ , which is what SPSS gives for the 'equal variances assumed' result.

### Cohen's Measure of Effect Size $d$

Cohen's  $d$ , a commonly-used measure of effect size, can be calculated for a two-group analysis from  $(Mean_1 - Mean_2) / SD$ , where SD is the pooled within-group standard deviation. Above, we calculated this SD to be .53601. The difference between the means in that example was .4416;  $d$  is therefore .82 which, according to Cohen's guidelines, is a large effect (according to the same guidelines, .2 is a small effect and .5 a medium-sized effect). One way of interpreting  $d$  is to say that it shows the difference between the two means in standard deviation units.

Note that it is also possible to calculate  $d$  directly from the  $t$ -value and the degrees of freedom. If there are equal numbers in each group,  $d = 2t / \sqrt{df}$ ; when the numbers are unequal, as in the present example,  $d = t * (n_1 + n_2) / [\sqrt{df} \sqrt{(n_1 n_2)}]$ . In the present case,  $d$  calculated with this formula is equal to .82, as above.

Report: The difference between the means was approximately .8 of a standard deviation (Cohen's  $d = .82$ ), which can be regraded as a substantial effect.

### 3.1.2 Correlated Responses

Example: Is the mean rating for *jobsat* (the mean of *e4* to *e7*) significantly different from the mean rating for discretionary effort (the mean of *e1* to *e3*)?

#### **Paired Samples t-test**

compute jobsat=mean(e4 to e7).  
compute disceff=mean(e1 to e3).

Point-and-click: Analyze → Compare Means → Paired-Samples T Test. Specify *jobsat* and *disceff* as the Paired Variables.

Syntax: t-test pairs=jobsat disceff.

**Paired Samples Statistics**

		Mean	N	Std. Deviation	Std. Error Mean
Pair 1	JOBSAT	2.8472	924	.56281	.01852
	DISCEFF	3.1425	924	.48576	.01598

**Paired Samples Correlations**

		N	Correlation	Sig.
Pair 1	JOBSAT & DISCEFF	924	.386	.000

Note: The original *t*-test output table was broken into the two following pieces to fit on the page.

**Paired Samples Test**

		Paired Differences				
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference	
					Lower	Upper
Pair 1	JOBSAT - DISCEFF	-.2953	.58458	.01923	-.3330	-.2575

**Paired Samples Test**

		t	df	Sig. (2-tailed)
Pair 1	JOBSAT - DISCEFF	-15.354	923	.000

Report: There was a significant difference between the mean ratings of *jobsat* and *disceff*,  $t(923) = 15.35, p < .0005$ . The mean for discretionary effort (3.14, sd .49) was higher than that for job satisfaction (2.85, sd .56).

It is of interest to note that the correlation between the responses was not very high ( $r = .39, p < .0005$ ); that is, there was a small tendency for those who gave high ratings on *e4* to *e7* to give high ratings on *e1* to *e3*.

Note: The standard error of the difference between the means is the standard deviation of the differences divided by square root of the number of cases (pairs):  $.58458/\sqrt{924} = .01923$ .

The Effect of the Correlation Between the Variables If we examine the standard deviation of the differences a bit further, we can see that the correlation between the two sets of responses is relevant to the test of the significance of the difference of the two means. The standard deviation of the difference between two variables is equal to

$$\sqrt{[(\sigma_1^2 + \sigma_2^2 - 2 r_{12} \sigma_1 \sigma_2)]}$$

where  $\sigma_1$  is the standard deviation of the first variable (*jobsat* in our example),  $\sigma_2$  is the standard deviation of the second variable (*disceff* in our example), and  $r_{12}$  is the correlation between the two variables. Notice that because the part of the formula containing the  $r$  is subtracted from the sum of the two variances,  $\sigma_1^2 + \sigma_2^2$ , the higher the correlation, the smaller the standard deviation of the difference. Also note that if  $r$  is zero, the second term disappears, and the SD of the difference is just the square root of the sum of the variances. (A further point is that if the correlation is negative, the second term is added onto the sum of the two variances, and the SD becomes greater.)

If we substitute the values given by SPSS into the equation, we get

$$\sqrt{[(.56281^2 + .48576^2 - 2*.386*.56281*.48576)]} = .5845$$

which, allowing for a bit of rounding error, is the value given in the output above.

The main point is that, because the  $t$ -statistic that we calculate to decide whether the difference is significant comes from

$$t = (\text{Difference between the means}) / (\text{SD of the difference}/\sqrt{N})$$

then, for a given difference between the means, the smaller the SD of the difference, the bigger the  $t$ -value and the more likely we are to find it significant. Because higher correlations lead to smaller SDs, they will lead to smaller standard errors and to higher values of  $t$ . This point is why, other things being equal, repeated measures analyses can be more sensitive (i.e., more likely to reject the null hypothesis) than independent groups analyses.

## 3.2 Differences Between Two Proportions

### 3.2.1 Independent Groups

Example: Are female employees more likely than male employees to report experiencing bullying, etc by a supervisor or manager?

### **Crosstabulation and Chi-Squared Test of Independence**

Point-and-click: Analyze → Descriptive Statistics → Crosstabs. Specify *q2* as the row variable and *L4* as the column variable. Click on Cells and check Row Percentages. Click on Statistics and specify Chi-square.

Syntax: crosstabs q2 by L4/cells=count row/statistics=chisq.



**Q2 gender \* L4 bullying by supervisor Crosstabulation**

			L4 bullying by supervisor		Total
			1 yes	2 no	
Q2 gender	1 female	Count	22	91	113
		% within Q2 gender	19.5%	80.5%	100.0%
	2 male	Count	158	646	804
		% within Q2 gender	19.7%	80.3%	100.0%
Total		Count	180	737	917
		% within Q2 gender	19.6%	80.4%	100.0%

**Chi-Square Tests**

	Value	df	Asymp. Sig. (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	.002 <sup>b</sup>	1	.963		
Continuity Correction <sup>a</sup>	.000	1	1.000		
Likelihood Ratio	.002	1	.963		
Fisher's Exact Test				1.000	.540
Linear-by-Linear Association	.002	1	.963		
N of Valid Cases	917				

a. Computed only for a 2x2 table

b. 0 cells (.0%) have expected count less than 5. The minimum expected count is 22.18.

Report: The percentage of female employees who had experienced bullying, etc by a supervisor or manager (19.5%) was very similar to the percentage of males who reported experiencing this behaviour (19.7%). The chi-squared test of independence was not significant,  $\chi^2(1; N=917) = .002, p = .963$ .

### 3.2.2 Correlated Proportions

Example: Does the proportion of employees who reported experiencing bullying, etc by a supervisor or manager differ from the proportion who reported experiencing bullying, etc by members of their work group?

#### McNemar's Test of Correlated Proportions

Point-and-click: Analyze → Nonparametric Tests → 2 Related Samples. Enter L3 and L4 into the Test Pair(s) List. Check McNemar. Uncheck Wilcoxon.

Syntax: npar tests mcnemar=L3 L4.

**.3 bullying by member dept & L4 bullying by supervisor**

L3 bullying by member dept	L4 bullying by supervisor	
	1	2
1	99	124
2	82	618

**Test Statistics<sup>b</sup>**

	L3 bullying by member dept & L4 bullying by supervisor
N	923
Chi-Square <sup>a</sup>	8.160
Asymp. Sig.	.004

a. Continuity Corrected

b. McNemar Test

Report: The proportion of employees who reported experiencing bullying, etc by a member of their work group is equal to  $(124 + 99)/923 = .2416$ , while the proportion who reported experiencing bullying by a supervisor or manager is equal to  $(82 + 99)/923 = .1961$  and was therefore lower. The result of McNemar's test,  $\chi^2(1; N=923) = 8.16, p = .004$ , indicates that this difference is significant.

Note: It is also possible to request McNemar's test for variables specified in the crosstabs procedure. In this example, you would specify *L3* and *L4* as the row and column variables, then click on Statistics, and check McNemar.

**4. Reporting Relationships Between Variables**

**4.1 Associations Between Numeric Variables**

Example: Are ratings of discretionary effort [*c1* to *c3*] associated with perceptions of opportunities for growth and development [*d1* to *d7*]?

compute disceff=mean(c1 to c3).

compute growth=mean(d1 to d7).

**Pearson Correlation and Confidence Interval**

Point and Click: Analyze→Correlate→Bivariate. Specify *growth* and *disceff* on the Variables list. Confirm that Pearson is checked.

Syntax: correlations growth disceff.

**Correlations**

		DISCEFF	GROWTH
DISCEFF	Pearson Correlation	1	.336**
	Sig. (2-tailed)	.	.000
	N	925	925
GROWTH	Pearson Correlation	.336**	1
	Sig. (2-tailed)	.000	.
	N	925	925

\*\* . Correlation is significant at the 0.01 level (2-tailed).

Report: There is a weak but significant correlation between *growth* and *disceff*,  $r = .336$ ,  $p < .0005$ , with higher ratings of opportunities for growth and development being associated with higher ratings of discretionary effort.

Variance Accounted For

The square of the correlation is .113, which indicates that the variables have only 11.3% of their variance in common.

Further Interpretation

A correlation coefficient is a standardised regression coefficient (i.e., what we would obtain if both variables were standardised to have a mean of zero and a standard deviation of one); so, one way of interpreting this result is to say that a one standard deviation increase in *growth* is associated with a .336 standard deviation increase in *disceff*.

Confidence Interval for a Correlation Coefficient

SPSS doesn't give confidence intervals for correlation coefficients, and it's a little complicated to calculate them, but it is good to know how to do it. Firstly, the coefficient is transformed to a z-score form,  $Z_r$ , using this formula:

$$Z_r = .5 * [\log_e(1 + r) - \log_e(1 - r)] = .5 * [.290 - (-.409)] = .35.$$

This transformation is performed because the z-score version of  $r$  is approximately normally distributed, while  $r$  itself is not. Secondly, the standard error for  $Z_r$ , which is equal to  $1/\sqrt{N - 3}$ , where  $N$  is the number of cases, is calculated. In this example  $s.e.(Z_r) = 1/\sqrt{(925 - 3)} = .033$ . Thirdly, the lower and upper limits of the confidence interval are obtained by subtracting (lower) and adding (upper) the  $s.e.(Z_r)$ , multiplied by the appropriate z-value (1.96 for the 95% confidence interval), from and to  $Z_r$ . In our example this calculation gives  $.35 - .033 * 1.96 = .285$  and  $.35 + .033 * 1.96 = .415$ . Fourthly, the upper and lower limits are translated from their z-score form to correlation coefficients, using the formula:

$$r = (e^{2Z_r} - 1) / (e^{2Z_r} + 1), \text{ where } e = 2.71828.$$

Your calculator will probably have a key marked  $e^x$  which you can use. In this example,  $r = (1.768 - 1)/(1.768 + 1) = .278$  for the lower limit and  $r = (2.29 - 1)/(2.29 + 1) = .392$  for the upper limit.

Report: The correlation between *growth* and *disceff*,  $r = .336$  (95% CI .278 - .392).

#### 4.2 Associations Between Binary (Dichotomous) Variables

Example: Are employees who reported experiencing racial harassment (*L1*) also likely to report experiencing sexual harassment (*L2*)? In other words, are responses to *L1* and *L2* associated?

#### Yule's *Q*

Point-and click: Analyze → Descriptive Statistics → Crosstabs. Specify *L1* as row variable and *L2* as the column variable. Click on Cells and check Row Percentages. Click on Statistics and specify gamma.

Syntax: crosstabs L1 by L2/statistics=gamma.

**L1 racial harassment \* L2 sexual harassment Crosstabulation**

			L2 sexual harassment		Total
			1 yes	2 no	
L1 racial harassment	1 yes	Count	74	78	152
		% within L1 racial harassment	48.7%	51.3%	100.0%
	2 no	Count	36	733	769
		% within L1 racial harassment	4.7%	95.3%	100.0%
Total		Count	110	811	921
		% within L1 racial harassment	11.9%	88.1%	100.0%

#### Symmetric Measures

		Value	Asymp. Std. Error <sup>a</sup>	Approx. T <sup>b</sup>	Approx. Sig.
Ordinal by Ordinal	Gamma	.902	.022	9.008	.000
N of Valid Cases		921			

a. Not assuming the null hypothesis.

b. Using the asymptotic standard error assuming the null hypothesis.

Report: Over 48% of employees who reported experiencing racial harassment also reported experiencing sexual harassment, and 95.3 % of those who did not report racial harassment did not report sexual harassment. There was a statistically significant association between the two responses; Yule's  $Q = .902$ ,  $p < .0005$ .

Note: Although we have asked for *gamma*, we will think of it in terms of Yule's *Q*, which is equal to *gamma* in 2 x 2 tables. Yule's *Q* for a 2 x 2 table

a	b
c	d

is equal to  $(ad - bc)/(ad + bc)$ . In other words, *Q* will be large if large numbers of cases fall into the *a* (yes, yes, in our example) and *d* (no, no) cells, compared to the *b* (yes, no) and *c* (no, yes) cells (or vice versa). In the present example  $Q = (74*733 - 78*36) / (74*733 + 8*36) = .902$ . While there are various indices of association for dichotomous variables, including the phi ( $\Phi$ ) coefficient, which is equal to the Pearson correlation between the variables, *Q* is often preferred because of its desirable properties. One of these properties is that it can take on its theoretical minimum and maximum (-1 and 1) regardless of the distribution of the variables, which is not true for  $\Phi$ .

#### 4.3. Associations Between Numeric and Binary (Dichotomous) Variables

Example: Is there an association between reporting experiencing bullying, etc, by a supervisor or manager (*L4*) and job satisfaction (*jobsat*)?

##### The Point-Biserial Correlation Coefficient

Point-and-click: Analyze → Correlate → Bivariate. Specify *L4* and *jobsat* on the Variables list. Confirm that Pearson is checked.

Syntax: correlations *L4 jobsat*.

		L4 bullying by supervisor	JOBSAT
L4 bullying by supervisor	Pearson Correlation	1	.312**
	Sig. (2-tailed)	.	.000
	N	923	919
JOBSAT	Pearson Correlation	.312**	1
	Sig. (2-tailed)	.000	.
	N	919	924

\*\* . Correlation is significant at the 0.01 level (2-tailed).

Report: There is a weak but significant association between reporting experiencing bullying by a supervisor or manager and ratings of job satisfaction,  $r = .312, p < .0005$ . Because reports of bullying were coded 1 for 'yes' and 2 for 'no', the positive correlation means that those who had not experienced bullying gave more favourable job satisfaction ratings than those who had experienced bullying.

Note: Although it can be computed with a special formula, the point-biserial correlation is nothing more than a Pearson correlation between a dichotomous and numeric variable. It is not used a great deal, because in the situations where it is

applicable we are more likely to use the independent groups *t*-test, with the dichotomous variable as the grouping variable and the numeric variable as the dependent variable, as we did for the same data in the example in Section 3.1.1. The *p*-values obtained with the two kinds of analysis of the same data are exactly the same. In the one case, though, we get the means, which are useful descriptively, and in the other we get an idea of the strength of the association between the two variables which, in the present case, appears quite weak ( $r^2 = .312^2 = .097$ , less than 10%); compare this value with Cohen's measure of effect size, which was calculated in Section 3.1.1. This comparison demonstrates that a relatively small value of  $r^2$  may be associated with a relatively large effect size as measured by Cohen's *d*.

## **5. Reporting Differences Between Three or More Estimates of Population Parameters**

### 5.1 Differences Between Three or More Means

#### 5.1.1 Independent Groups

Example: Do ratings of work/job flexibility (*flex*) differ for employees who, in the last 12 months, have seriously considered leaving Ajax, those who have fleetingly considered leaving Ajax and those who did not consider leaving Ajax (*m1*)?

### **One Way Independent Groups ANOVA**

compute flex=mean(c1 to c4).

Point and Click: Analyze→General Linear Model→Univariate. Specify *flex* as the Dependent Variable and *m1* as a Fixed Factor. Click on the Plots button, and specify *m1* to be plotted on the Horizontal Axis. Click on Add and Continue. Click on the Options button, and check Descriptive Statistics.

Syntax: glm flex by m1/print=descriptives/plot=profile(m1).

**Between-Subjects Factors**

		Value Label	N
M1 last 6 mths	1	not at all	438
considered leaving	2	yes fleet	317
job	3	yes serios	165

**Descriptive Statistics**

Dependent Variable: FLEX

M1 last 6 mths	Mean	Std. Deviation	N
1 not at all	3.2190	.57667	438
2 yes fleet	2.9629	.59715	317
3 yes serios	2.8545	.66493	165
Total	3.0654	.61846	920

**Tests of Between-Subjects Effects**

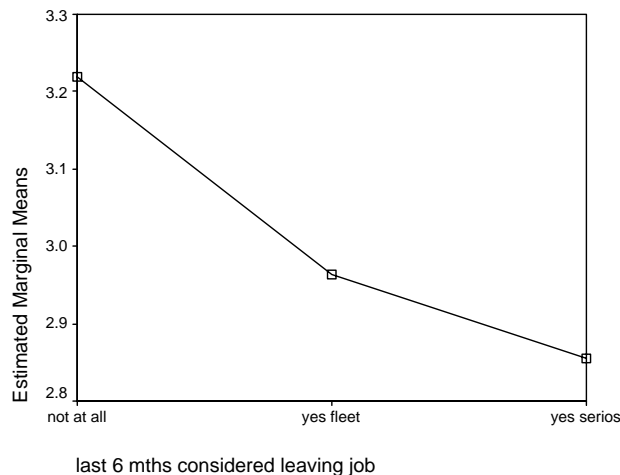
Dependent Variable: FLEX

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	20.996 <sup>a</sup>	2	10.498	29.127	.000
Intercept	7101.732	1	7101.732	19703.550	.000
M1	20.996	2	10.498	29.127	.000
Error	330.513	917	.360		
Total	8996.444	920			
Corrected Total	351.510	919			

a. R Squared = .060 (Adjusted R Squared = .058)

**Profile Plots**

Estimated Marginal Means of FLEX



Report: The mean ratings of job/work flexibility were 3.22 (SD .58), 2.96 (.60) and 2.85 (.66), respectively, for those who had not thought of leaving Ajax, those who had done so fleetingly and those who had done so seriously. There was a significant overall difference between the means,  $F(2, 917) = 29.1, p < .0005$ . As can be seen from the graph, mean ratings of flexibility fell from the 'not at all' group, to the 'fleetingly' group then, less sharply, to the 'seriously' group.

Note: The graph above shows the 'Estimated Marginal Means' (EMMs) of *flex*. These are means which are calculated from the regression equation for this analysis. When there are covariates and/or other factors in an analysis, the EMMs are very

useful, because they are adjusted for these other variables. It is therefore possible to compare the adjusted (EMMs) and unadjusted (observed) means to see what effect the other variables are having on group differences when they 'held constant'. In this example, there are no covariates or other factors, so the EMMs are the same as the observed means shown in the Descriptive Statistics table.

5.1.1.1 Comparisons Between Pairs of Means, Adjusted for the Number of Comparisons

Repeat the commands in 5.1.1, with the following additions:

Point-and-Click: Click on the Post Hoc button, specify *ml* in the Post Hoc Tests for box, and check Bonferroni.

Syntax: `posthoc=ml(bonferroni)/`

Note: Part of the following table has been deleted so that it fits on the page.

**Multiple Comparisons**

Dependent Variable: FLEX

Bonferroni

(I) last 6 mths considered leaving job	(J) last 6 mths considered leaving job	Mean Difference (I-J)	Std. Error	Sig.
1 not at all	2 yes fleet	.2561*	.04427	.000
	3 yes serios	.3644*	.05484	.000
2 yes fleet	1 not at all	-.2561*	.04427	.000
	3 yes serios	.1084	.05763	.181
3 yes serios	1 not at all	-.3644*	.05484	.000
	2 yes fleet	-.1084	.05763	.181

Based on observed means.

\*. The mean difference is significant at the .05 level.

Notes: (1) The GLM procedure Bonferroni-adjusts for the number of pairwise comparisons by multiplying the obtained *p*-value by the number of comparisons, then comparing this adjusted value with the default *alpha*, .05 in this case. In this example, there were three possible pairwise comparisons, so the obtained *p*-value for the difference between fleetingly and seriously groups (for example) of .0603 was multiplied by three to get the value in the table, .181.

(2) SPSS provides the mean differences and the standard errors of the differences. If you want to quote a *t*- or *F*-value, you can divide the difference by the standard error, which produces a *t*-value, then square that *t*-value to obtain an *F*-value. The degrees of freedom for the *t*-value are those for the error term in the ANOVA, 917 in this example.



Report: Bonferroni-adjusted pairwise comparisons showed that there was a significant difference between the ratings of the 'yes, fleetingly' and 'yes, seriously' groups on the one hand and the 'not at all' group on the other [ $t(917) = 5.79, p < .0005$  and  $t(917) = 6.64, p < .0005$ , respectively], but that there was no difference between the two 'yes' groups ( $t(917) = 1.88, p = .181$ ).

### 5.1.2 Correlated Responses

Example: Are employees' ratings of communication different for communication between men and women ( $f1$ ), people of different ages ( $f2$ ) and people from different cultural or racial backgrounds ( $f3$ )?

### One Way Repeated Measures ANOVA

Point-and-Click: Analyze → General Linear Model → Repeated Measures. Give *scale* as the Within-Subject Factor Name, and 3 as the Number of Levels. Click on Add, then Define. Specify  $f1$ ,  $f2$  and  $f3$  as the Within-Subjects Variables. Click on the Plots button, and specify *scale* to be plotted on the Horizontal Axis. Click on Add and Continue. Click on the Options button, and check Descriptive Statistics.

Syntax: `glm f1 f2 f3/wsfactor=scale 3/plot=profile(scale)/print=descriptives.`

Note: Some tables have been omitted from the output.

#### Within-Subjects Factors

Measure: MEASURE\_1

SCALE	Dependent Variable
1	F1
2	F2
3	F3

#### Descriptive Statistics

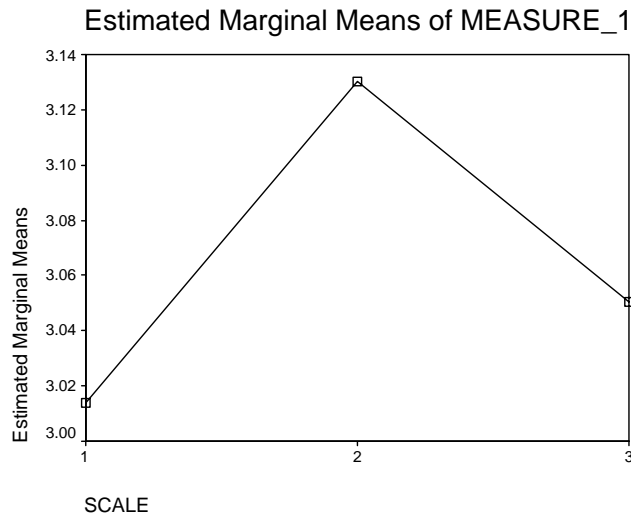
	Mean	Std. Deviation	N
F1 commun good bet sexes	3.01	.563	876
F2 commun good bet ages	3.13	.455	876
F3 commun good bet cultures	3.05	.487	876

**Tests of Within-Subjects Effects**

Measure: MEASURE\_1

Source		Type III Sum of Squares	df	Mean Square	F	Sig.
SCALE	Sphericity Assumed	6.213	2	3.107	32.660	.000
	Greenhouse-Geisser	6.213	1.875	3.314	32.660	.000
	Huynh-Feldt	6.213	1.879	3.307	32.660	.000
	Lower-bound	6.213	1.000	6.213	32.660	.000
Error(SCALE)	Sphericity Assumed	166.454	1750	.095		
	Greenhouse-Geisser	166.454	1640.513	.101		
	Huynh-Feldt	166.454	1643.911	.101		
	Lower-bound	166.454	875.000	.190		

**Profile Plots**



Report: The mean ratings of communication were 3.01 (SD .56) for men and women, 3.13 (.46) for people of different ages and 3.05 (.49) for people from different cultural or racial backgrounds. There was a significant overall difference between the means,  $F(2, 1750) = 32.7, p < .0005$ . As can be seen from the graph, there appear to be differences between the mean ratings for people of different ages, on the one hand, and those for men and women, and for different cultures, on the other hand.

5.1.2.1 Comparisons Between Pairs of Means, Adjusted for the Number of Comparisons

Repeat the commands in 5.1.2, with the following additions:

Point-and-Click: Click on the Options button, specify *scale* in the Display Means for box, check Compare Main Effects, and select Bonferroni from the pull-down menu.

Syntax: `emmeans=table(scale) compare(scale) adjust(bonferroni)/`

**Pairwise Comparisons**

Measure: MEASURE\_1

(I) SCALE	(J) SCALE	Mean Difference (I-J)	Std. Error	Sig. <sup>a</sup>	95% Confidence Interval for Difference <sup>a</sup>	
					Lower Bound	Upper Bound
1	2	-.116*	.015	.000	-.152	-.081
	3	-.037	.016	.075	-.076	.002
2	1	.116*	.015	.000	.081	.152
	3	.080*	.013	.000	.049	.111
3	1	.037	.016	.075	-.002	.076
	2	-.080*	.013	.000	-.111	-.049

Based on estimated marginal means

\*. The mean difference is significant at the .050 level.

a. Adjustment for multiple comparisons: Bonferroni.

Report: The mean rating for people of different ages was significantly higher than that for men and women ( $t(875) = 7.73, p < .0005$ ) and people from different cultural or racial backgrounds ( $t(875) = 6.15, p < .0005$ ). There was no difference between the ratings for men and women and people from different cultural or racial backgrounds ( $t(875) = 2.31, p = .075$ ).

Note: The error terms for pairwise comparisons are not pooled, so that the degrees of freedom for the  $t$ -values are [error df/(df for scale)] = 875.

5.2 Differences Between Three or More Proportions

5.2.1 Independent Groups

Example: Are employees who have considered leaving Ajax (fleetingly or seriously) more likely to have experienced sexual harassment than those who have not considered leaving Ajax?

**Crosstabulation and Chi-Squared Test of Independence and Follow-Up Analyses**

Point-and-Click: Analyze → Descriptive Statistics → Crosstabs. Specify *m1* as the row variable and *L2* as the column variable. Click on Cells and check Row Percentages. Click on Statistics and specify Chi-square.

Syntax: crosstabs m1 by L2/cells=count row/statistics=chisq.

**M1 last 6 mths considered leaving job \* L2 sexual harassment Crosstabulation**

			L2 sexual harassment		Total
			1 yes	2 no	
M1 last 6 mths considered leaving job	1 not at all	Count	34	405	439
		% within M1 last 6 mths considered leaving job	7.7%	92.3%	100.0%
	2 yes fleet	Count	46	271	317
		% within M1 last 6 mths considered leaving job	14.5%	85.5%	100.0%
	3 yes serio	Count	30	134	164
		% within M1 last 6 mths considered leaving job	18.3%	81.7%	100.0%
Total		Count	110	810	920
		% within M1 last 6 mths considered leaving job	12.0%	88.0%	100.0%

**Chi-Square Tests**

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	15.617 <sup>a</sup>	2	.000
Likelihood Ratio	15.673	2	.000
Linear-by-Linear Association	15.197	1	.000
N of Valid Cases	920		

a. 0 cells (.0%) have expected count less than 5. The minimum expected count is 19.61.

Report: The percentage of employees who had experienced sexual harassment varied from 7.7% for those who had not considered leaving Ajax, through 14.5% for those who had considered leaving only fleetingly, to 18.3% for those who had seriously considered leaving. The overall difference between the proportions was significant,  $\chi^2 (2; N=920) = 15.6, p < .0005$ .

Note: We could have asked the original question in a different form; namely, "Were employees who had experienced sexual harassment more likely to consider leaving Ajax than those who had not?" It would then have been more sensible to ask for column rather than row percentages, so that we could compare those who had experienced sexual harassment with those who had not, rather than comparing those who had considered leaving with those who had not, etc:

**M1 last 6 mths considered leaving job \* L2 sexual harassment Crosstabulation**

			L2 sexual harassment		Total
			1 yes	2 no	
M1 last 6 mths considered leaving job	1 not at all	Count	34	405	439
		% within L2 sexual harassment	30.9%	50.0%	47.7%
	2 yes fleet	Count	46	271	317
		% within L2 sexual harassment	41.8%	33.5%	34.5%
	3 yes serio	Count	30	134	164
		% within L2 sexual harassment	27.3%	16.5%	17.8%
Total		Count	110	810	920
		% within L2 sexual harassment	100.0%	100.0%	100.0%

Note that the chi-squared test of independence would have been exactly the same as the one we obtained originally – it is a test of either hypothesis.

### 5.2.1 Follow-Up Tests

Various sorts of follow-up tests are possible in a table like the one we've obtained. We could make pairwise comparisons, such as the comparison of those who had seriously considered leaving with those who had not. We could also carry out more complex comparisons, such as comparing all those who had considered leaving at all with those who had not.

#### 5.2.1.1 Pairwise Comparisons

Perhaps the easiest way of carrying out pairwise comparisons is to temporarily select the two groups which are to be compared, then rerun the original analysis. As an example, we'll compare the two 'yes' groups by omitting the 'no' group.

Point-and-Click: **Data** → **Select Cases**. Check **If condition is satisfied** and click on **If...** Enter **m1 = 2 or m1 = 3**. Run the crosstabs again.

Syntax:

```
temporary.  
select if (m1 eq 2 or m2 eq 3).
```

**M1 last 6 mths considered leaving job \* L2 sexual harassment Crosstabulation**

			L2 sexual harassment		Total
			1 yes	2 no	
M1 last 6 mths considered leaving job	2 yes fleet	Count	46	271	317
		% within M1 last 6 mths considered leaving job	14.5%	85.5%	100.0%
	3 yes serios	Count	30	134	164
		% within M1 last 6 mths considered leaving job	18.3%	81.7%	100.0%
Total		Count	76	405	481
		% within M1 last 6 mths considered leaving job	15.8%	84.2%	100.0%

**Chi-Square Tests**

	Value	df	Asymp. Sig. (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	1.162 <sup>b</sup>	1	.281		
Continuity Correction <sup>a</sup>	.895	1	.344		
Likelihood Ratio	1.141	1	.285		
Fisher's Exact Test				.293	.172
Linear-by-Linear Association	1.159	1	.282		
N of Valid Cases	481				

a. Computed only for a 2x2 table

b. 0 cells (.0%) have expected count less than 5. The minimum expected count is 25.91.

Report: There was no difference between the 'yes, fleetingly' and 'yes, seriously' groups in terms of the proportion who had experienced sexual harassment,  $\chi^2 (1; N=481) = 1.16, p = .281$ .

Note: In order to be significant, the *p*-value for each pairwise comparison has to be less than  $.05/npc$ , where *npc* is the number of possible pairwise comparisons, three in this case.

### 5.2.1.2 Complex Comparisons

Sometimes we might want to combine groups for comparisons. A natural example in the present case would be to combine the two 'yes' groups and compare them to the 'no' group. We could make this comparison by using *recode* to create a variable which has the same code for the two 'yes' groups, then rerun the original analysis. Note that with syntax it is possible to recode a variable temporarily, so that a new variable doesn't have to be created.

Point-and-Click: Transform → Recode → Into Different Variables. Specify that 1 is to be copied into a new variable, *m1\_yn*, and that 2 and 3 are to be coded as 2.

Syntax:

temporary.  
 recode m1 (3=2).

**M1\_YN \* L2 sexual harassment Crosstabulation**

			L2 sexual harassment		Total
			1 yes	2 no	
M1_YN	1.00	Count	34	405	439
		% within M1_YN	7.7%	92.3%	100.0%
	2.00	Count	76	405	481
		% within M1_YN	15.8%	84.2%	100.0%
Total		Count	110	810	920
		% within M1_YN	12.0%	88.0%	100.0%

**Chi-Square Tests**

	Value	df	Asymp. Sig. (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	14.148 <sup>b</sup>	1	.000		
Continuity Correction <sup>a</sup>	13.394	1	.000		
Likelihood Ratio	14.533	1	.000		
Fisher's Exact Test				.000	.000
Linear-by-Linear Association	14.133	1	.000		
N of Valid Cases	920				

a. Computed only for a 2x2 table

b. 0 cells (.0%) have expected count less than 5. The minimum expected count is 52.49.

Note: If we want to carry out complex as well as pairwise comparisons, we can adjust for both types of comparison by using the chi-squared equivalent of the Scheffé test. To be significant at .05 in a 2 x 3 table, as in this example, the chi-squared for a follow-up 2 x 2 table has to be greater than  $\chi^2$  (.05,  $df=6$ ), which is equal to 12.59. The degrees of freedom for this critical value are equal to  $r \times c$ , where  $r$  is the number of rows and  $c$  is the number of columns. Using the same method, the critical value for  $p = .01$  is 16.81, and for  $p = .001$ , 22.46.

Report: Almost 16% of those who had fleetingly or seriously considered leaving Ajax had experienced sexual harassment, compared with almost 8% of those who had not considered leaving. This difference was significant,  $\chi^2$  (1; N=920) = 14.15,  $p < .05$ .

### 5.2.2 Correlated Responses

Example: Are the proportions of employees who have experienced bullying or intimidation, etc by a member of their work group/department, who have experienced bullying or intimidation, etc by a supervisor or manager, or who have experienced victimisation, different from each other?

### Cochran's Q Test with Follow-up McNemar Tests

Point-and-click: Analyze → Nonparametric Tests → K Related Samples. Select L3, L4 and L5 as Test Variables. Check Cochran's Q. Uncheck Friedman.

Syntax: npar tests cochran=L3 L4 L5.

**Frequencies**

	Value	
	1	2
L3 bullying by member dept	222	697
L4 bullying by supervisor	177	742
L5 victimisation	107	812

**Test Statistics**

N	919
Cochran's Q	77.500 <sup>a</sup>
df	2
Asymp. Sig.	.000

a. 2 is treated as a success.

The proportions can be calculated from the first table. They are  $222/(222+697) = .242$ ,  $177/(177+742) = .193$  and  $107/(107+812) = .116$ .

Report: The percentages of employees who reported each kind of behaviour were 24.2%, 19.3% and 11.6%, respectively. There was an overall significant difference among the percentages, Cochran's Q (2; N=919) = 77.5,  $p < .0005$ .

#### Follow-up Tests

Having obtained a significant overall difference, we may want to carry out pairwise tests. The McNemar test (Section 3.2.2 of these notes) is appropriate for these follow-up analyses.

Point-and-click: Point-and-click: Analyze → Nonparametric Tests → 2 Related Samples. Enter L3, L4 and L5 into the Test Pair(s) List. Check McNemar. Uncheck Wilcoxon.

Syntax: npar tests mcnemar=L3 L4 L5.

Note: Only part of the output is shown below.



**Test Statistics<sup>b</sup>**

	L3 bullying by member dept & L4 bullying by supervisor	L3 bullying by member dept & L5 victimisation	L4 bullying by supervisor & L5 victimisation
N	923	919	919
Chi-Square <sup>a</sup>	8.160	71.801	35.007
Asymp. Sig.	.004	.000	.000

a. Continuity Corrected

b. McNemar Test

Note: The McNemar test is performed on all three pairwise combinations of the three variables. To adjust for the number of comparisons, we would divide *alpha* by the number of comparisons, which gives .0167 as the critical *p*-value.

Report: Bonferroni-adjusted pairwise comparisons of the proportions showed that all three were significant; the proportion for L3 was significantly higher than that for both L4 ( $\chi^2(1; N=923) = 8.16, p = .004$ ) and L5 ( $\chi^2(1; N=919) = 71.8, p < .0005$ ), and that for L4 was higher than that for L5 ( $\chi^2(1; N=919) = 35.0, p < .0005$ ).

Note: By default, the McNemar tests were performed on all cases which had valid data for each pairwise comparison. It would have been better if we had asked that the tests be performed only on cases which had valid (i.e., non-missing) data for all three variables. We could have done this analysis as follows:

Point-and-click: Set up the tests as described above, but also click on the Options button and select Exclude cases listwise.

Syntax: `npar tests mcnemar=L3 L4 L5/missing=listwise.`

## **6. Reporting Relationships Between A Dependent Variable and More Than One Independent Variable**

### 6.1 Partial Correlation

Example: To what extent is the relationship between ratings of opportunity for growth and discretionary effort due to their correlation with ratings of job satisfaction? [The correlation of *jobsat* with *growth* is .641,  $p < .0005$ , and with *disceff* .386,  $p < .0005$ .]

#### **The Partial Correlation Coefficient**

Point-and-click: Analyze → Correlate → Partial. Select *growth* and *disceff* in the Variables box, and *jobsat* in the Controlling for box.

Syntax: `partial corr growth disceff by jobsat.`

- - - P A R T I A L C O R R E L A T I O N C O E F F I C I E N T S - -

Controlling for.. JOBSAT

	GROWTH	DISCEFF
GROWTH	1.0000 ( 0) P= .	.1248 ( .921) P= .000
DISCEFF	.1248 ( .921) P= .000	1.0000 ( 0) P= .

(Coefficient / (D.F.) / 2-tailed Significance)

" . " is printed if a coefficient cannot be computed

Report: The partial correlation between ratings of opportunities for growth and discretionary effort when ratings of job satisfaction were held constant was  $r = .125$ ,  $p < .0005$ . This value is lower than the bivariate correlation of .336 between *growth* and *disceff*.

## 6.2 Multiple Numeric and Dichotomous IVs

Example: How much of the variability of ratings of job satisfaction can be attributed to variability in ratings of work flexibility, hours on call, opportunities for growth and development, communications, tension and conflict and whether employees have experienced some form of harassment, bullying, etc? Do each of these variables make a unique contribution to predicting job satisfaction? What is the contribution of each variable?

### Multiple Regression

```
compute jobsat=mean(e4 to e7).
compute flex=mean(c1 to c4).
compute hrs_call=mean(c5,c6).
compute growth=mean(d1 to d7).
compute commun=mean(f1 to f6).
compute tension=mean(g1 to g6).
count harass=11 to 16 (1).
recode harass (2 thru hi=1).
```

Point-and-click: Analyze → Regression → Linear. Specify *jobsat* as Dependent and select *flex*, *hrs\_call*, *growth*, *commun*, *tension* and *harass* as Independents. Confirm that Method Enter is selected. Click on Statistics, check Part and partial correlations, and confirm that Estimates and Model fit are checked.

```
Syntax: regression vars=jobsat flex hrs_call growth commun tension harass/
statistics=coeff outs r anova zpp/
dep=jobsat/method=enter.
```

Note: One table has been omitted.

**Model Summary**

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.704 <sup>a</sup>	.496	.493	.40040

a. Predictors: (Constant), HARASS, HRS\_CALL, COMMUN, GROWTH, TENSION, FLEX

**ANOVA<sup>b</sup>**

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	142.767	6	23.795	148.416	.000 <sup>a</sup>
	Residual	145.093	905	.160		
	Total	287.860	911			

a. Predictors: (Constant), HARASS, HRS\_CALL, COMMUN, GROWTH, TENSION, FLEX

b. Dependent Variable: JOBSAT

Note: The original Coefficients table was broken into the two following pieces to fit on the page.

**Coefficients<sup>a</sup>**

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.694	.167		4.166	.000
	FLEX	.126	.025	.139	4.982	.000
	HRS_CALL	-.010	.022	-.012	-.439	.660
	GROWTH	.491	.028	.485	17.778	.000
	COMMUN	.242	.039	.176	6.232	.000
	TENSION	-.066	.031	-.059	-2.169	.030
	HARASS	-.114	.029	-.100	-3.902	.000

a. Dependent Variable: JOBSAT

**Coefficients<sup>a</sup>**

Model		Correlations		
		Zero-order	Partial	Part
1	FLEX	.366	.163	.118
	HRS_CALL	-.166	-.015	-.010
	GROWTH	.646	.509	.420
	COMMUN	.460	.203	.147
	TENSION	-.304	-.072	-.051
	HARASS	-.318	-.129	-.092

a. Dependent Variable: JOBSAT

Report: Considered together, the predictors accounted for 49.6% of the variance of the job-satisfaction ratings. The value of .493 for the adjusted  $R^2$  suggests that this value is a reasonable estimate of the  $R^2$  in the population<sup>3</sup>. The overall model was significant,  $F(6, 905) = 148.4, p < .0005$ .

Using an *alpha* level of .01, all of the variables except ratings of hours on call ( $B = -.01, t(905) = .44, p = .66$ ) and of tension and conflict ( $B = -.07, t(905) = 2.17, p = .030$ ) made significant contributions in the model, adjusted for the other variables. The regression coefficients<sup>4</sup> were positive in sign for *flex* ( $B = .13, t(905) = 4.98, p < .0005$ ), *growth* ( $B = .49, t(905) = 17.78, p < .0005$ ) and *commun* ( $B = .24, t(905) = 6.23, p < .0005$ ), meaning that higher ratings on these scales went with greater job satisfaction, while the negative coefficient for *harass* ( $B = -.11, t(905) = 3.92, p < .0005$ ) indicated that employees who had experienced harassment or bullying gave lower ratings of job satisfaction.

The squared part and partial correlations tell us how much of the variance of *jobsat* was accounted for by each variable, adjusted for the other variables. The squared part correlation is equal to the sum of squares for the predictor (not obtainable from the output) divided by the total sum of squares. The squared partial correlation (sometimes called *partial eta*<sup>2</sup>) is equal to the sum of squares for the predictor divided by the total sum of squares from which the sums of squares for the other predictors have been subtracted. The partial correlation will therefore always be larger than the part correlation. In the present example, the value of .485 for the standardised regression coefficient for *growth* indicated that it made the strongest single contribution to predicting job satisfaction when the other variables were held constant. It accounted for 17.6% (part) or 25.9% (partial) of the variance of job satisfaction ratings when adjusted for the other variables in the model<sup>5</sup>.

Alan Taylor, 28th October, 2004

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<sup>3</sup> The adjusted  $R^2$  is calculated with the formula  $R^2_{\text{adj}} = R^2 - [(1 - R^2)p]/(C - p')$ , where  $C$  is the number of cases,  $p$  is the number of independent variables and  $p'$  is the number of coefficients in the model, including that for the intercept. The adjusted  $R^2$  will tend to small compared to the sample value for models which have a large number of predictors in relation to the number of cases.

<sup>4</sup> Because the unstandardised, or raw, regression coefficients are reported, 'B' is used to stand for the coefficients rather than  $\beta$  (Beta).

<sup>5</sup> The squared part correlation can be calculated with the following formula:

$100 * t^2 * (1 - R^2)/(C - p - 1)$  where  $t$  is the  $t$ -statistic for the independent variable and  $C$  and  $p$  are as defined above (so that  $[C - p - 1]$  are the degrees of freedom for the error term). The  $R^2$  in the formula is expressed as a fraction rather than as a percentage. The percentage of variance accounted for by *growth* fitted last is then

$100 * 17.778^2 * (1 - .496)/(905) = 17.6\%$