

## Self-Assessment

### Weeks 9: Multiple Regression with Both Qualitative and Quantitative Predictors; Multiple Comparisons

1. What is an adjusted mean? What potential benefit does it offer? How could it potentially be misleading?

**An adjusted mean is a predicted mean using the regression model that takes into account partial contributions of both qualitative and quantitative predictors (covariates in ANCOVA language). Often researchers will use mean values of quantitative predictors (covariates) when calculating adjusted means although any value of the quantitative predictors could be used to calculate adjusted means.**

**One benefit of the adjusted mean is that it provides an estimated mean for group comparisons in which groups have the same value on quantitative predictors (covariates). So adjusted means provide a way to statistically equate groups on covariates when such groups are not equivalent. This is helpful when determining whether a treatment would be effective if all groups had similar background characteristics. For example, if each of the experimental classes had similar levels of IQ (the covariate), which treatment appears to be most beneficial? Thus, the adjusted mean is a way to equalize groups on covariates that may not be similar across groups.**

**Adjusted means may be misleading because the adjustments made to nonequivalent groups may not be realistic. For example, it may not be reasonable to assume all groups would have similar covariate mean scores, so covariate means used to obtain adjusted means may be unrealistic and provide misleading equivalence among nonequivalent groups. As a concrete example, comparing treatments between regular middle school students and special education middle school students while assuming both groups have mean IQ = 100 when calculating adjusted means could be unrealistic.**

**In experimental research in which subjects are assigned randomly to treatment groups, such adjustments are almost always believed to be acceptable. In correlational and quasi-experimental studies that use intact groups, adjustments are more likely to be misleading so caution should always be used when working with adjusted means.**

2. Below is linked blood pressure data that was presented in previous self-assessments. Perform comparisons of systolic blood pressure among drugs (Ziac, Losartan, Lisinopril 40mg, Lisinopril 12.5mg) while controlling for weight, i.e.,

Systolic Blood Pressure =  $b_0 + b_j \text{ Drug} + b_i \text{ Weight}$

Where  $b_j$  represents several drug coefficients and  $b_i$  is an unnumbered coefficient for Weight.

Use the Bonferroni adjustment and set familywise alpha to .05. Present results in APA style. Also, present a table showing the predicted systolic blood pressure for someone who weighs 220, 200, and 180 pounds for each of the four treatments.

SPSS

<http://www.bwgriffin.com/gsu/courses/edur8132/selfassessments/Week09/BloodPressureDrugs.sav>

Excel

<http://www.bwgriffin.com/gsu/courses/edur8132/selfassessments/Week09/BloodPressureDrugs.xlsx>

## Results

**Table 1: Descriptive Statistics for Systolic Blood Pressure, Weight, and Drug Treatments**

Variable	1	2	3	4	5
1. Systolic Blood Pressure	---				
2. Weight	.04	---			
3. Lisinopril 40mg	-.22	.39*	---		
4. Losartan	.08	-.92*	-.33*	---	
5. Ziac	.07	.15	-.29*	-.33*	---
Mean	153.36	220.75	.22	.28	.22
SD	11.48	7.91	.42	.45	.42

*Note:* Lisinopril 40mg, Losartan, and Ziac are dummy variables (1, 0); n = 76.

\*p<.05

**Table 2: Regression of Systolic Blood Pressure on Weight and Drug Treatments**

Variable	b	se	$\Delta R^2$	95%CI	F	t
Drug			.197		5.82*	
2 = Lisinopril 40mg	-6.01	3.45		-12.89, 0.87		-1.74
3 = Losartan	28.54	8.27		12.04, 45.04		3.45*
4 = Ziac	5.66	3.71		-1.74, 13.06		1.52
Weight	1.63	0.44	.152	0.75, 2.52		3.68*
Intercept	-215.32	100.60		-415.90, -14.76		-2.14*

*Note:*  $R^2 = .20$ , adj.  $R^2 = .15$ ,  $F_{4,71} = 4.41^*$ ,  $MSE = 111.58$ ,  $n = 76$ .  $\Delta R^2$  represents the squared semi-partial correlation or the increment in  $R^2$  due to adding the respective variable; Lisinopril 40mg, Losartan, and Ziac are dummy variables (1, 0).

\*p < .05.

**Table 3: Comparisons of Adjusted Mean Differences in Systolic Blood Pressure among Drug Treatments**

Contrast	Estimated Mean Difference	Standard Error of Difference	95% Bonferroni Corrected CI of Mean Difference
Lis. 40mg vs. Lis. 12.5mg	-6.01	3.45	-15.37, 3.35
Losartan vs. Lis. 12.5mg	28.54*	8.27	6.09, 51.00
Ziac vs. Lis. 12.5mg	5.66	3.71	-4.42, 15.73
Losartan vs. Lis. 40mg	34.55*	8.48	11.54, 57.56
Ziac vs. Lis. 40mg	11.67*	3.93	1.00, 22.33
Ziac vs. Losartan	-22.88*	7.12	-42.20, -3.57

\*p < .05, where p-values are adjusted using the Bonferroni method.

Regression results show that both weight and drug treatment are associated with systolic blood pressure. The greater the weight, the higher blood pressure. The table of comparisons reveal that Losartan resulted in statistically higher blood pressure than the other three drug treatments tested even after controlling for weight. Additionally, the remaining three drug treatments appear to result in similar mean levels of systolic blood pressure after controlling for weight since there are no statistically significant differences noted in Table 3 except for the Ziac vs. Lisinopril (40mg) comparison which shows that systolic blood pressure is higher when taking Ziac than when taking Lisinopril (40mg).

## Predicted Systolic Blood Pressure

The predicted mean systolic blood pressure for each drug treatment and for weights of 180, 200, and 220 are tabled below.

Table 4: Predicted Systolic Blood Pressure for Drug Treatments and Different Weights

Weight	Drug Treatment			
	Lisinopril 12.5	Lisinopril 40	Losartan	Ziac
180	78.93	72.92	107.47	84.59
200	111.63	105.62	140.17	117.28
220	144.32	138.31	172.86	149.98

## Stata Commands and Results

```
. regress meanhighsystolic i.drug_num weight
2 = Lisinopril 40
3 = Losartan
4 = Ziac
. corr meanhighsystolic weight lisinopril40 losartan ziac, means
. pwcorr meanhighsystolic weight lisinopril40 losartan ziac, sig
. testparm i.drug_num
. di 5.83 * (1-.1989) / 71*3      " = Delta R-squared "
. testparm weight
. di 13.51 * (1-.1989) / 71*1    " = Delta R-squared "
. margins drug_num, mcompare(bonferroni) pwcompare level(95)
. margins drug_num, at( weight=(180)) asbalanced
. margins drug_num, at( weight=(200)) asbalanced
. margins drug_num, at( weight=(220)) asbalanced
```

```
. regress meanhighsystolic i.drug_num weight
```

Source	SS	df	MS	Number of obs	=	76
-----+-----				F(4, 71)	=	4.41
Model	1967.38559	4	491.846397	Prob > F	=	0.0031
Residual	7922.02231	71	111.577779	R-squared	=	0.1989
-----+-----				Adj R-squared	=	0.1538
Total	9889.40789	75	131.858772	Root MSE	=	10.563

meanhighsy~c	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
-----+-----						
drug_num						
2	-6.009033	3.449123	-1.74	0.086	-12.88639	.8683232
3	28.54137	8.273454	3.45	0.001	12.04457	45.03817
4	5.656523	3.711093	1.52	0.132	-1.743186	13.05623
weight	1.634732	.4448129	3.68	0.000	.7478002	2.521664
_cons	-215.3194	100.5965	-2.14	0.036	-415.9031	-14.7357

```
. corr meanhighsystolic weight lisinopril40 losartan ziac, means
(obs=76)
```

Variable	Mean	Std. Dev.	Min	Max
meanhighsy~c	153.3553	11.48298	127.5	180.5
weight	220.75	7.911384	205	236
lisinopril40	.2236842	.4194817	0	1
losartan	.2763158	.4501462	0	1
ziac	.2236842	.4194817	0	1

	meanhi~c	weight	lisin~40	losartan	ziac
meanhighsy~c	1.0000				
weight	0.0395	1.0000			
lisinopril40	-0.2146	0.3867	1.0000		
losartan	0.0826	-0.9238	-0.3317	1.0000	
ziac	0.0719	0.1537	-0.2881	-0.3317	1.0000

```
. pwcorr meanhighsystolic weight lisinopril40 losartan ziac, sig
```

	meanhi~c	weight	lisin~40	losartan	ziac
meanhighsy~c	1.0000				
weight	0.0395	1.0000			
lisinopril40	-0.2146	0.3867	1.0000		
losartan	0.0826	-0.9238	-0.3317	1.0000	
ziac	0.0719	0.1537	-0.2881	-0.3317	1.0000

```
. testparm i.drug_num
( 1) 2.drug_num = 0
( 2) 3.drug_num = 0
( 3) 4.drug_num = 0
```

```
F( 3, 71) = 5.83
Prob > F = 0.0013
```

```
. di 5.83 * (1-.1989) / 71*3 " = Delta R-squared "
.19734139 = Delta R-squared
```

```
. testparm weight
( 1) weight = 0
```

```
F( 1, 71) = 13.51
Prob > F = 0.0005
```

```
. di 13.51 * (1-.1989) / 71*1 " = Delta R-squared "
.15243466 = Delta R-squared
```

```
. margins drug_num, mcompare(bonferroni) pwcompare level(95)
```

Pairwise comparisons of predictive margins

Model VCE : OLS

Expression : Linear prediction, predict()

```
-----+-----
      |      Number of
      |      Comparisons
-----+-----
drug_num |              6
-----+-----
```

```
-----+-----
      |      Delta-method      Bonferroni
      |      Contrast  Std. Err.  [95% Conf. Interval]
-----+-----
drug_num |
  2 vs 1 | -6.009033   3.449123   -15.37061   3.352543
  3 vs 1 | 28.54137    8.273454    6.085642   50.9971
  4 vs 1 |  5.656523   3.711093   -4.416089   15.72913
  3 vs 2 | 34.5504     8.477104   11.54193   57.55888
  4 vs 2 | 11.66556    3.928091    1.00397   22.32714
  4 vs 3 | -22.88485   7.117365   -42.20273  -3.566963
-----+-----
```

```
. margins drug_num, at( weight=(180)) asbalanced
```

Adjusted predictions Number of obs = 76

Model VCE : OLS

Expression : Linear prediction, predict()

at : drug\_num (asbalanced)

weight = 180

```
-----+-----
      |      Delta-method
      |      Margin  Std. Err.  t  P>|t|  [95% Conf. Interval]
-----+-----
drug_num |
  1 | 78.93236   20.63292   3.83  0.000   37.79149   120.0732
  2 | 72.92332   20.80291   3.51  0.001   31.44351   114.4031
  3 | 107.4737   13.1039    8.20  0.000   81.34529   133.6022
  4 | 84.58888   19.29777   4.38  0.000   46.11023   123.0675
-----+-----
```

```

. margins drug_num, at( weight=(200)) asbalanced
Adjusted predictions          Number of obs    =          76
Model VCE      : OLS

Expression  : Linear prediction, predict()
at          : drug_num          (asbalanced)
              weight            =          200

```

```

-----+-----
              |              Delta-method
              |      Margin   Std. Err.      t    P>|t|     [95% Conf. Interval]
-----+-----
drug_num |
  1 |      111.627   11.83416     9.43  0.000     88.03036     135.2236
  2 |      105.618   12.02438     8.78  0.000     81.64202     129.5939
  3 |      140.1684   4.619498    30.34  0.000     130.9573     149.3794
  4 |      117.2835   10.54659    11.12  0.000     96.25422     138.3128
-----+-----

```

```

. margins drug_num, at( weight=(220)) asbalanced

Adjusted predictions          Number of obs    =          76
Model VCE      : OLS

Expression  : Linear prediction, predict()
at          : drug_num          (asbalanced)
              weight            =          220

```

```

-----+-----
              |              Delta-method
              |      Margin   Std. Err.      t    P>|t|     [95% Conf. Interval]
-----+-----
drug_num |
  1 |      144.3216   3.558659    40.56  0.000     137.2259     151.4174
  2 |      138.3126   3.833733    36.08  0.000     130.6684     145.9568
  3 |      172.863    5.408706    31.96  0.000     162.0783     183.6477
  4 |      149.9782   2.88862     51.92  0.000     144.2184     155.7379
-----+-----

```

3. Below is a data file containing the following variables for cars taken between 1970 and 1982:

mpg: miles per gallon  
engine: engine displacement in cubic inches  
horse: horsepower  
weight: vehicle weight in pounds  
accel: time to accelerate from 0 to 60 mph in seconds  
year: model year (70 = 1970, to 82 = 1982)  
origin: country of origin (1=American, 2=Europe, 3=Japan)  
cylinder: number of cylinders

SPSS Data: [http://www.bwgriffin.com/gsu/courses/edur8132/selfassessments/Week04/cars\\_missing\\_deleted.sav](http://www.bwgriffin.com/gsu/courses/edur8132/selfassessments/Week04/cars_missing_deleted.sav)

(Note: There are underscore marks between words in the SPSS data file name.)

Other Data Format: If you prefer a data file format other than SPSS, let me know.

For this problem we wish to know whether MPG differs among car origins and number of cylinders while controlling for the weight of the car. The regression model for this study follows:

$$\text{Predicted MPG} = b_0 + \text{origin of car} + \text{number of cylinders} + \text{car weight}$$

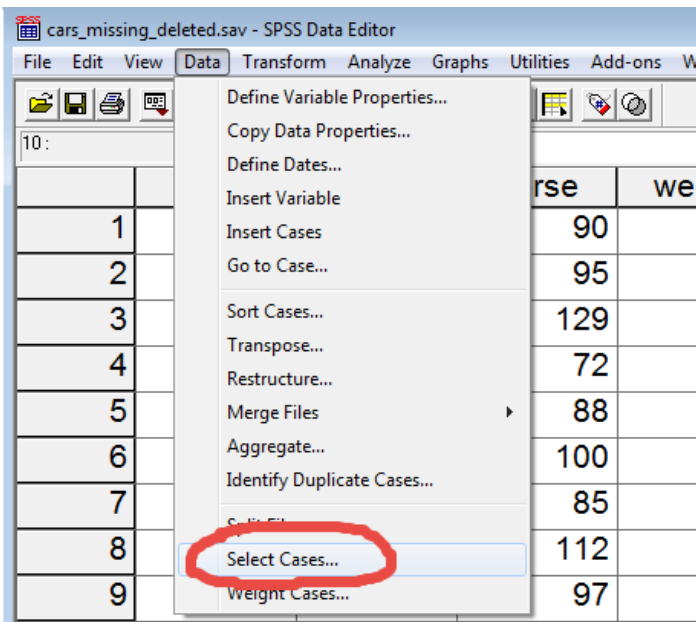
Origin of car is categorical. Number of cylinders may appear to be ratio, but since observed categories of this variable are limited, it is best to treat this variable as categorical. Note the following number of cylinders reported:

	Frequency	Percent	Valid Percent	Cumulative Percent
Valid 3 Cylinders	4	1.0	1.0	1.0
4 Cylinders	199	50.9	50.9	51.9
5 Cylinders	3	.8	.8	52.7
6 Cylinders	83	21.2	21.2	73.9
8 Cylinders	102	26.1	26.1	100.0
Total	391	100.0	100.0	

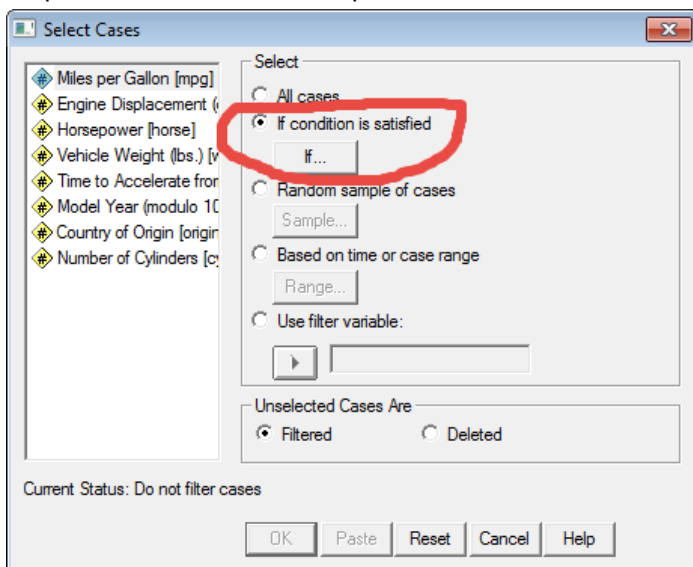
As the frequency display above shows, the number of cylinders include 3, 4, 5, 6, and 8. However, only 4 cars had 3 cylinders and only 3 cars had 5 cylinders. Given the small sample sizes for these categories, it is best to remove these cases from the regression analysis. There are several ways to accomplish this. Four approaches are (a) manually delete these cases after sorting all cases on number of cylinders, (b) telling SPSS to treat these 7 cases as missing values so they will not be included in any analysis (use Recode into Same Variable and set 3 Cylinders and 5 Cylinders as system missing), (c) defining 3 and 5 Cylinders as missing values in the variable missing values, or (d) using the Select Cases command to filter these cases from all analyses. Other possibilities also exist.

Of these four, option (d) works well and does not require deletion of any cases. This option is explained below.

Step 1: Open the Select Case window



Step 2: Choose the select If option



Step 3: Define the filter so SPSS can determine which cases NOT to select.

We do not want cylinders of 3 or 5, so in the Select Cases IF box, write

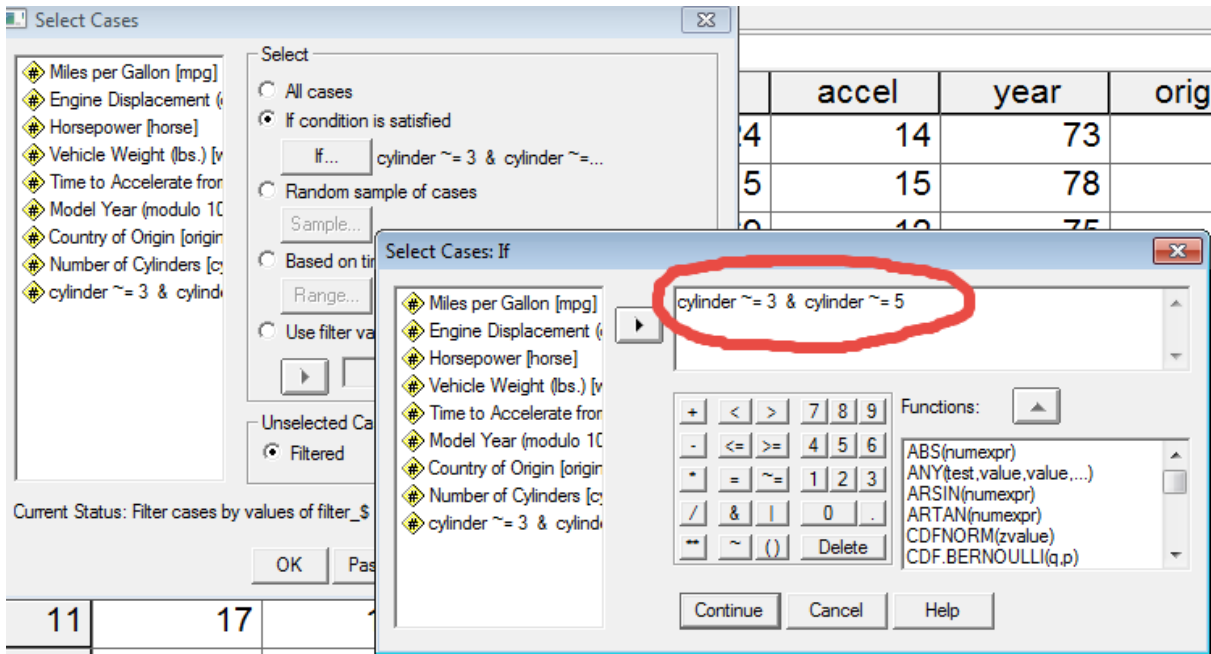
cylinders  $\neq$  3

The symbol  $\neq$  means “not equal”; this tells SPSS not to select any cases in which cylinders are 3. Also, write

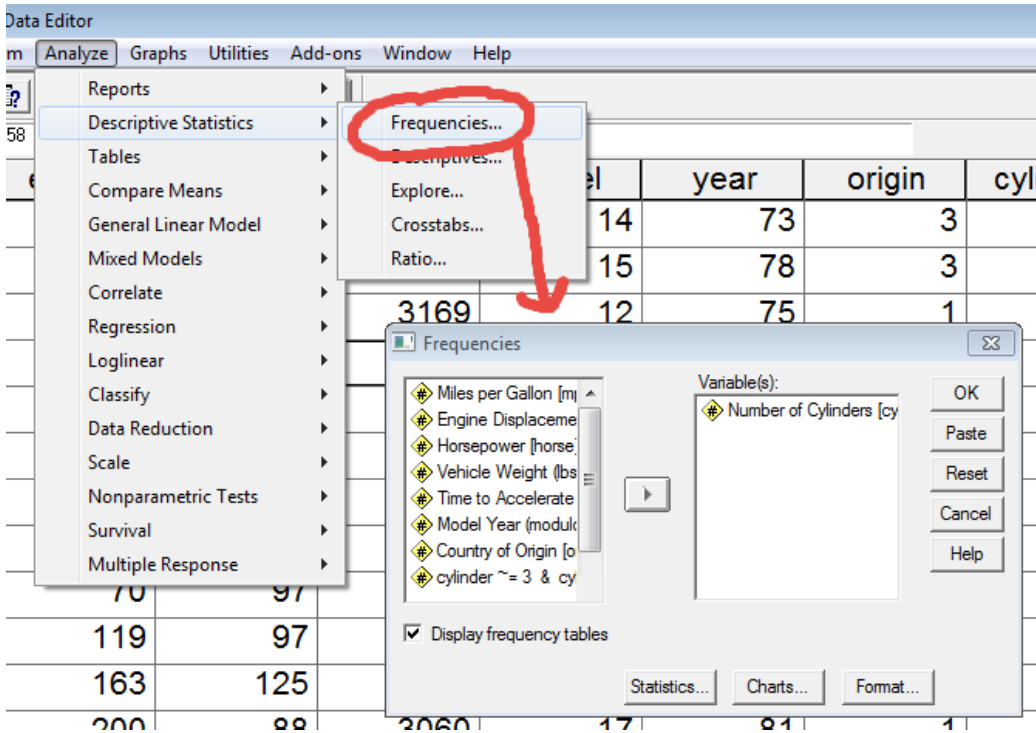
cylinders  $\neq$  5

so SPSS knows not to select cases when cylinders are 5. To combine these two, we use the ampersand symbol, &, which means select all cases which are not 3 and 5 cylinders. See image below.





Once these cases are defined, click Continue then OK to process this command. Next, check that the appropriate cases were selected by running the Frequency command for cylinders as shown below.



And the results should look like this:

→ Frequencies

Statistics

Number of Cylinders

N	Valid	384
	Missing	0

Number of Cylinders

	Frequency	Percent	Valid Percent	Cumulative Percent
Valid 4 Cylinders	199	51.8	51.8	51.8
6 Cylinders	83	21.6	21.6	73.4
8 Cylinders	102	26.6	26.6	100.0
Total	384	100.0	100.0	

Note that no cases of cylinders equal to 3 or 5 were selected.

Present an APA styled regression analysis with DV = MPG, IV = origin, IV = Cylinders (4, 6, and 8 only), and IV = vehicle weight. Set alpha = .01. You will have to create the dummy variables for origins and cylinders. Also present Scheffé confidence intervals comparisons among origins and among cylinders.

In addition to APA styled results, present literal interpretations for each regression coefficient.

Results

Table 1: Descriptive Statistics for MPG, Origin, and Number of Cylinders

Variable	1	2	3	4	5	6
1. MPG	---					
2. Origin 2 (Europe)	.24*	---				
3. Origin 3 (Japan)	.47*	-.22*	---			
4. Cylinder 6	-.24*	-.17*	-.16*	---		
5. Cylinder 8	-.65*	-.27*	-.30*	-.32*	---	
6. Weight	-.84*	-.31*	-.44*	.14*	.80*	---
Mean	23.48	0.17	0.20	0.22	0.27	2978.07
SD	7.81	0.38	0.40	0.41	0.44	850.69

Note: Origin 2 and 3 are dummy variables (1, 0) and Cylinder 6 and 8 are dummy variables (1, 0); n = 384.

\*p<.01

**Table 2: Regression of MPG on Origins and Cylinders**

Variable	b	se	$\Delta R^2$	99%CI	F	t
Origin			.010		7.42*	
2 = Europe	-.214	.662		-1.93, 1.50		-0.32
3 = Japan	2.144	.650		0.46, 3.83		3.30*
Number of Cylinders			.017		12.41*	
6	-3.719	.758		-5.68, -1.76		-4.91*
8	-3.415	1.142		-6.37, -0.46		-2.99*
Weight8	-0.005	.0006	.067	-0.007, -0.004		-9.84*
Intercept	41.604	1.461		37.82, 45.39		28.47*

*Note:*  $R^2 = .74$ , adj.  $R^2 = .73$ ,  $F_{5,378} = 212.97^*$ ,  $MSE = 16.20$ ,  $n = 384$ .  $\Delta R^2$  represents the squared semi-partial correlation or the increment in  $R^2$  due to adding the respective variable.

\* $p < .01$ .

**Table 3: Comparisons of Adjusted MPG among Vehicle Origins**

Contrast	Estimated Mean Difference	Standard Error of Difference	99% Scheffé Corrected CI of Mean Difference
Europe vs USA	-0.21	0.66	-2.24, 1.81
Japan vs USA	2.14*	0.65	0.16, 4.13
Japan vs Europe	2.36*	0.69	0.24, 4.47

\* $p < .01$ , where p-values are adjusted using the Scheffé method.

**Table 4: Comparisons of Adjusted MPG among Number of Cylinders**

Contrast	Estimated Mean Difference	Standard Error of Difference	99% Scheffé Corrected CI of Mean Difference
6 vs 4	-3.72*	0.76	-6.03, -1.40
8 vs 4	-3.42	1.14	-6.90, 0.07
8 vs 6	0.30	0.78	-2.09, 2.70

\* $p < .01$ , where p-values are adjusted using the Scheffé method.

Results show that there are statistical differences in MPG by vehicles' origin and number of cylinders, and that vehicle weight is negatively associated with MPG. The greater the vehicle weight, the lower will be MPG. For origins, cars from Japan appear to have about a 2 MPG advantage over cars from Europe and the USA once vehicle weight and number of cylinders are taken into account, and there seems to be little to no difference in MPG between cars from Europe and the USA. For number of cylinders, cars with 4 cylinders appear to obtain about 3 MPGs more than cars with 6 and 8 cylinders once vehicle origin and weight is controlled, but only the comparison between 4 and 6 cylinders shows a statistically significant difference at the .01 level of significance. There appears to be no difference in MPG between cars with 6 and 8 cylinders after controlling for weight and origins.

#### Literal Interpretations

**b<sub>0</sub> = 41.60:** The predicted MPG for a car made in USA, with 4 cylinders, and with a weight of 0.

**b<sub>1</sub> = -.214:** European cars expected to obtain .214 MPG less than American cars controlling for weight and cylinders.

**b2 = 2.14:** Japanese cars expected to obtain 2.14 MPG more than American cars controlling for weight and cylinders.

**b3 = -3.72:** Cars with 6 cylinders expected to obtain 3.72 MPG less than cars with 4 cylinders controlling for weight and origins.

**b4 = -3.41:** Cars with 8 cylinders expected to obtain 3.41 MPG less than cars with 4 cylinders controlling for weight and origins.

**b5 = -0.005:** For every 1 additional pound added to weight of a car, the MPG is expected to decline by .005 controlling for vehicle origin and cylinders.

## STATA Commands and Results

```
. regress mpg i.origin i.cylinder weight if cylinder==4 | cylinder==6 | cylinder==8, level(99)
. tabulate origin , gen(origin)
. tabulate cylinder , gen( cylinder )
. corr mpg origin2 origin3 cylinder4 cylinder5 weight if cylinder==4 | cylinder==6 | cylinder==8,
means
. pwcorr mpg origin2 origin3 cylinder4 cylinder5 weight if cylinder==4 | cylinder==6 |
cylinder==8, sig
. testparm i.origin
. di 7.42 * (1-.7380) / 378*2 " = Delta R-squared"
. testparm i.cylinder
. di 12.41 * (1-.7380) / 378*2 " = Delta R-squared"
. testparm weight
. di 96.76 * (1-.7380) / 378*1 " = Delta R-squared"
. margins origin , mcompare(scheffe) pwcompare level(99)
. margins cylinder , mcompare(scheffe) pwcompare level(99)

. regress mpg i.origin i.cylinder weight if cylinder==4 | cylinder==6 | cylinder==8, level(99)
```

Source	SS	df	MS	Number of obs	=	384
-----				F(5, 378)	=	212.97
Model	17251.2188	5	3450.24377	Prob > F	=	0.0000
Residual	6123.76114	378	16.2004263	R-squared	=	0.7380
-----				Adj R-squared	=	0.7346
Total	23374.98	383	61.0312793	Root MSE	=	4.025

mpg	Coef.	Std. Err.	t	P> t	[99% Conf. Interval]
-----					
origin					
2	-.2140693	.6625454	-0.32	0.747	-1.929332 1.501193
3	2.14367	.6502408	3.30	0.001	.4602624 3.827077
cylinder					
6	-3.719466	.7581589	-4.91	0.000	-5.682262 -1.75667
8	-3.415028	1.142405	-2.99	0.003	-6.372598 -.457459
weight	-.0056387	.0005732	-9.84	0.000	-.0071227 -.0041547
_cons	41.60402	1.461099	28.47	0.000	37.82138 45.38665

```
. tabulate origin , gen(origin)
```

Country of Origin	Freq.	Percent	Cum.
1	244	62.40	62.40
2	68	17.39	79.80
3	79	20.20	100.00
<b>Total</b>	<b>391</b>	<b>100.00</b>	

```
. tabulate cylinder , gen( cylinder )
```

Number of Cylinders	Freq.	Percent	Cum.
3	4	1.02	1.02
4	199	50.90	51.92
5	3	0.77	52.69
6	83	21.23	73.91
8	102	26.09	100.00
<b>Total</b>	<b>391</b>	<b>100.00</b>	

```
. corr mpg origin2 origin3 cylinder4 cylinder5 weight if cylinder==4 | cylinder==6 | cylinder==8,
means
(obs=384)
```

Variable	Mean	Std. Dev.	Min	Max
mpg	23.48307	7.812252	10	46.6
origin2	.1692708	.3754802	0	1
origin3	.1953125	.3969583	0	1
cylinder4	.2161458	.4121519	0	1
cylinder5	.265625	.4422416	0	1
weight	2978.065	850.694	1613	5140

	mpg	origin2	origin3	cy lind~4	cy lind~5	weight
mpg	1.0000					
origin2	0.2390	1.0000				
origin3	0.4733	-0.2224	1.0000			
cylinder4	-0.2362	-0.1696	-0.1630	1.0000		
cylinder5	-0.6522	-0.2715	-0.2963	-0.3158	1.0000	
weight	-0.8412	-0.3058	-0.4444	0.1385	0.8003	1.0000

Note: cylinder4 = 6 cylinders and cylinder5 = 8 cylinders.

```
. pwcorr mpg origin2 origin3 cylinder4 cylinder5 weight if cylinder==4 | cylinder==6 |
cylinder==8, sig
```

	mpg	origin2	origin3	cylind~4	cylind~5	weight
mpg	1.0000					
origin2	0.2390	1.0000				
origin3	0.4733	-0.2224	1.0000			
cylinder4	-0.2362	-0.1696	-0.1630	1.0000		
cylinder5	-0.6522	-0.2715	-0.2963	-0.3158	1.0000	
weight	-0.8412	-0.3058	-0.4444	0.1385	0.8003	1.0000

```
. testparm i.origin
```

```
( 1) 2.origin = 0
```

```
( 2) 3.origin = 0
```

```
F( 2, 378) = 7.42
```

```
Prob > F = 0.0007
```

```
. di 7.42 * (1-.7380) / 378*2 " = Delta R-squared"
```

```
.01028593 = Delta R-squared
```

```
. testparm i.cylinder
```

```
( 1) 6.cylinder = 0
```

```
( 2) 8.cylinder = 0
```

```
F( 2, 378) = 12.41
```

```
Prob > F = 0.0000
```

```
. di 12.41 * (1-.7380) / 378*2 " = Delta R-squared"
```

```
.01720328 = Delta R-squared
```

```
. testparm weight
```

```
( 1) weight = 0
```

```
F( 1, 378) = 96.76
```

```
Prob > F = 0.0000
```

```
. di 96.76 * (1-.7380) / 378*1 " = Delta R-squared"
```

```
.06706646 = Delta R-squared
```

```
. margins origin , mcompare(scheffe) pwcompare level(99)
```

```
Pairwise comparisons of predictive margins
```

```
Model VCE : OLS
```

```
Expression : Linear prediction, predict()
```

	Delta-method		Scheffe	
	Contrast	Std. Err.	[99% Conf. Interval]	
origin				
2 vs 1	-.2140693	.6625454	-2.237109	1.80897
3 vs 1	2.14367	.6502408	.1582014	4.129138
3 vs 2	2.357739	.6922867	.2438863	4.471592

. margins cylinder , mcompare(scheffe) pwcompare level(99)

Pairwise comparisons of predictive margins

Model VCE : OLS

Expression : Linear prediction, predict()

```
-----
```

		Delta-method	Scheffe	
	Contrast	Std. Err.	[99% Conf. Interval]	
cylinder				
6 vs 4	-3.719466	.7581589	-6.034455 -1.404477	
8 vs 4	-3.415028	1.142405	-6.903287 .0732304	
8 vs 6	.3044378	.7841679	-2.089968 2.698844	

```
-----
```