Solutions for Session 6

08/11/2022

- . do solution.do
- . global basedir http://personalpages.manchester.ac.uk/staff/mark.lunt
- . global datadir \$basedir/stats/6_LinearModels2/data
- . sysuse auto, clear (1978 Automobile Data)
- . regress weight foreign

Source	SS	df	f MS			Number of obs		74
Model Residual	15496779.3 28597399.1	1 72		6779.3 86.099		F(1, 72) Prob > F R-squared	=	39.02 0.0000 0.3514 0.3424
Total	44094178.4	73	6040	29.841		Adj R-squared Root MSE	=	630.23
weight	Coef.	Std.	Err.	t	P> t	[95% Conf.	In	terval]
foreign _cons	-1001.206 3317.115	160.2 87.39		-6.25 37.95	0.000	-1320.734 3142.893		81.6788 491.338

1.1 foreign vehicles are, on average, 1000 lbs lighter than US vehicles The difference is significant, $p\,=\,0.000$

. regress weight i.foreign

Source	SS	df	f MS			Number of obs		74
Model Residual	15496779.3 28597399.1	1 72		06779.3 .86.099		F(1, 72) Prob > F R-squared Adj R-squared	=	39.02 0.0000 0.3514 0.3424
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foreign Foreign _cons	-1001.206 3317.115	160.2 87.39		-6.25 37.95	0.000	-1320.734 3142.893		81.6788 491.338

1.2 This makes no difference at all

. ttest weight, by(foreign)

Two-sample t test with equal variances

Group	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf.	Interval]
Domestic Foreign	52 22	3317.115 2315.909	96.4296 92.31665	695.3637 433.0035	3123.525 2123.926	3510.706 2507.892
combined	74	3019.459	90.34692	777.1936	2839.398	3199.521
diff		1001.206	160.2876		681.6788	1320.734

diff = mean(Domestic) - mean(Foreign) degrees of freedom =

t = 6.2463 72

Ho: diff = 0

Ha: diff != 0

Ha: diff > 0

Ha: diff < 0 Pr(T < t) = 1.0000Pr(|T| > |t|) = 0.0000Pr(T > t) = 0.0000

- 1.3 the mean difference and standard error are exactly the same (except for the minus sign)
- . graph box weight, over(foreign)
- . graph export graph1.eps replace (file graph1.eps written in EPS format)
- 1.4 There is a wider spread of weights for Domestic cars compared to Foreign cars, i.e. greater variance
- . by foreign: summ weight

> foreign = Don	mestic					
Variable	Obs	Mean	Std. Dev.	Min	Max	
weight	52	3317.115	695.3637	1800	4840	
> foreign = For	reign					
Variable	Obs	Mean	Std. Dev.	Min	Max	
weight	22	2315.909	433.0035	1760	3420	

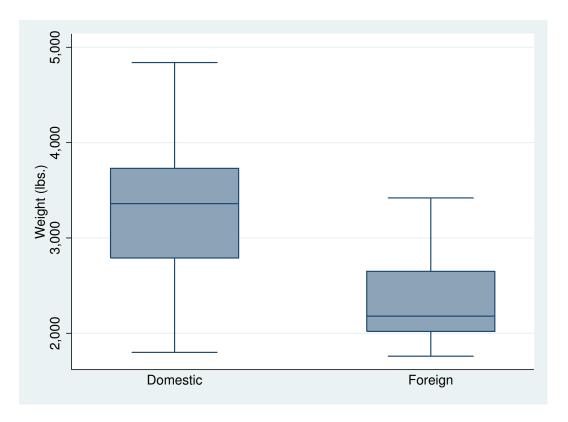


Figure 1: . graph box weight, over(foreign)

1.5 the SD is much higher for Domestic (~700) compared to Foreign (~430)

. hettest

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
Ho: Constant variance
Variables: fitted values of weight
chi2(1) = 4.51
Prob > chi2 = 0.0337

- 1.6 The difference in variance is significant. Therefore, a linear model is inappropriate
- . use \$datadir/soap, clear
- . graph box appearance, over(operator)

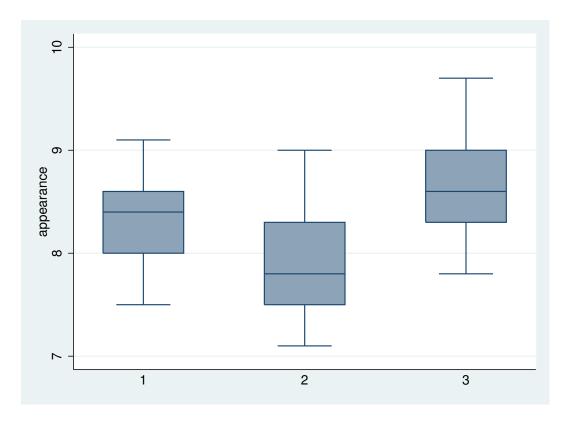


Figure 2: . graph box appearance, over(operator)

- . graph export graph2.eps replace (file graph2.eps written in EPS format)
 - 1.7 Operator 3 has the highest scores: 25% of scores are above 9 $\,$
- . sort operator

. by operator: summ appearance

-> operator =	1						
Variable	Obs	Mean	Std.	Dev.	Min	Max	
appearance	30	8.306667	.4630	0732	7.5	9.1	
-> operator =	2						
Variable	Obs	Mean	Std.	Dev.	Min	Max	
appearance	30	7.896667	. 4766	3863	7.1	9	
-> operator =	3						
Variable	Obs	Mean	Std.	Dev.	Min	Max	
appearance	30	8.626667	. 4653	3018	7.8	9.7	
. regress appe	arance i.oper	ator					
Source	SS	df	MS		Number of		
Model Residual	8.03400033 19.0869988		01700016 19390791		F(2, Prob > F R-squared	=	18.31 0.0000 0.2962
residual	19.0009900	01 .2.	19390791		Adj R-squ		
Total	27.1209991	89 .30	04730327		Root MSE	=	.46839
appearance	Coef.	Std. Err	. t	P> t	[95% (onf. I	nterval]
operator							
2	41	.1209382			65037		.1696222
3	.3200001	.1209382	2.6	0.010	.07962	23	.5603779
_cons	8.306667	.0855162	97.14	1 0.000	8.1366	94	8.476639

- 1.9 Yes: Prob > F = 0.0000 is testing the null hypothesis that all operators are the same.
- 1.10 p= 0.0000
- 1.11 Operator 1 is the baseline: there is no line for operator 1
- . lincom _cons + 2.operator
- (1) 2.operator + _cons = 0

appearance	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
(1)	7.896667	.0855162	92.34	0.000	7.726694	8.066639

1.12 This is the same as we have already seen

- . lincom 2.operator 3.operator
- (1) 2.operator 3.operator = 0

appearance	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
(1)	73	.1209382	-6.04	0.000	9703778	4896222

1.13 Yes: t = -6.04, p = 0.000

- . use \$datadir/cadmium, clear
- . scatter capacity age

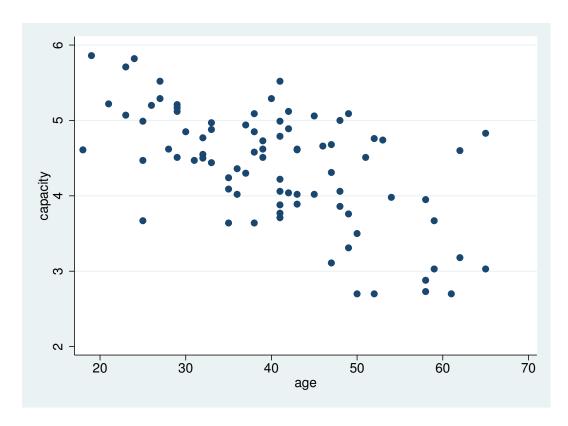


Figure 3: . scatter capacity age

. graph export graph3.eps replace (file graph3.eps written in EPS format)

. regress capacity age

Source	SS	df	MS			Number of obs = 84
Model Residual	17.4445864 30.1963679	1 82		445864 248388		F(1, 82) = 47.37 Prob > F = 0.0000 R-squared = 0.3662
Total	47.6409543	83	.573	987401		Adj R-squared = 0.3584 Root MSE = .60683
capacity	Coef.	Std.	Err.	t	P> t	[95% Conf. Interval]
age _cons	0404781 6.033316	.0058		-6.88 24.38	0.000	05217760287787 5.540986 6.525647

2.2 The regression coefficient for age is negative, showing that capacity decreases as age increases.

- . gen cap1 = capacity if exposure == 1
 (40 missing values generated)
- . gen cap2 = capacity if exposure == 2
 (56 missing values generated)
- . gen cap3 = capacity if exposure == 3
 (72 missing values generated)
- . scatter cap1 cap2 cap3 age
- . graph export graph4.eps replace (file graph4.eps written in EPS format)
- . regress capacity i.exposure

Source	SS	df	MS			Number of obs =	84
Model Residual	2.74733751 44.8936168	2 81		366875 242182		R-squared = 0	2.48 0.0902 0.0577 0.0344
Total	47.6409543	83	.573	987401			74447
capacity	Coef.	Std.	Err.	t	P> t	[95% Conf. Inte	rval]
exposure < 10 years > 10 years	.0097403 5128788	.1799		0.05 -2.12	0.957 0.037		78329 04741
_cons	4.462045	.1122	2337	39.76	0.000	4.238735 4.6	85355

2.3 Its borderline, p = 0.09

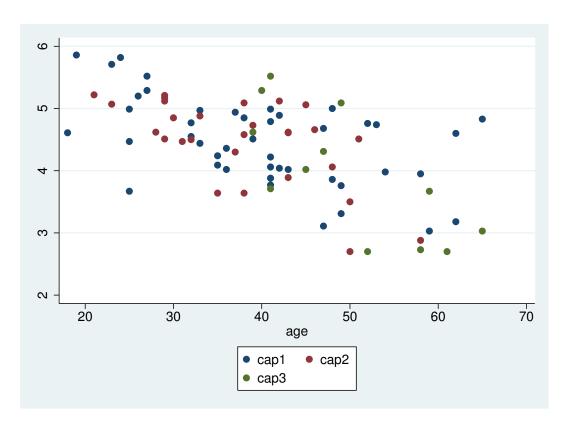


Figure 4: . scatter cap1 cap2 cap3 age

. regress capa	regress capacity age i.exposure									
Source	SS	df		MS		Number of obs = 8				
Model Residual	17.6062849 30.0346693	3 80	5.86876164 .375433367			F(3, 80) = 15.6 Prob > F = 0.000 R-squared = 0.369 Adi R-squared = 0.345				
Total	47.6409543	83	.573	987401		Adj R-squared = 0.345 Root MSE = .6127				
capacity	Coef.	Std.	Err.	t	P> t	[95% Conf. Interval]				
age	0397752	.0063	224	-6.29	0.000	0523572027193				
exposure < 10 years > 10 years	0701975 1169349	.1486		-0.47 -0.56	0.638 0.578	3660575 .225662 5333281 .299458				
_cons	6.044917	.2680	248	22.55	0.000	5.51153 6.57830				

- . testparm i.exposure
- (1) 2.exposure = 0 (2) 3.exposure = 0

- 2.4 There are now no significant differences between groups
- . predict ppred, xb
- . gen ppred1 = ppred if exposure == 1 (40 missing values generated)
- . gen ppred2 = ppred if exposure == 2 (56 missing values generated)
- . gen ppred3 = ppred if exposure == 3 (72 missing values generated)
- . scatter cap1 cap2 cap3 age || line ppred1 age || line ppred2 age || /* */ line ppred3 age
- . graph export graph5.eps replace (file graph5.eps written in EPS format)
- . regress capacity i.exposure##c.age

Source	SS	df	MS	Nu	mber of obs =	= 84
				F(5, 78) =	11.39
Model	20.1057424	5 4.02	114849	Pr	ob > F =	0.0000
Residual	27.5352118	78 .3530	015536	R-	squared =	0.4220
				Ad	j R-squared =	0.3850
Total	47.6409543	83 .573	987401	Ro	ot MSE =	.59415
capacity	Coef.	Std. Err	. t	P> t	[95% Conf.	Intervall
			· 			
exposure						
< 10 years	.5497403	.5758844	0.95	0.343	5967574	1.696238
> 10 years	2.503148	1.041842	2.40	0.019	.4289997	4.577296
·						
age	0306127	.0075475	-4.06	0.000	0456385	0155868
•						
exposure#c.age						
< 10 years	0159193	.0145469	-1.09	0.277	0448799	.0130413
> 10 years	0544983	.0210698	-2.59	0.012	0964451	0125516
•	1					

.313426

. testparm i.exposure#c.age

_cons

- (1) 2.exposure#c.age = 0
- (2) 3.exposure#c.age = 0

$$F(2, 78) = 3.54$$

 $Prob > F = 0.0338$

5.680291

18.12 0.000

5.056307

6.304274

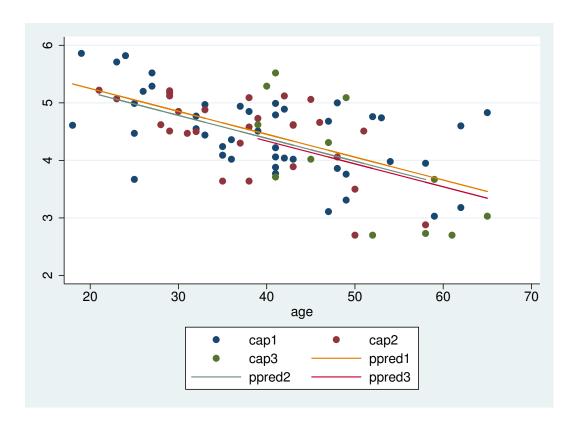


Figure 5: . scatter cap1 cap2 cap3 age —— line ppred1 age —— line ppred2 age —— /*

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2.5 Yes, the slopes in the different exposure groups are different

. predict ipred, xb

. gen ipred1 = ipred if exposure == 1
(40 missing values generated)

. gen ipred2 = ipred if exposure == 2
(56 missing values generated)

. gen ipred3 = ipred if exposure == 3
(72 missing values generated)

. scatter cap1 cap2 cap3 age || line ipred1 age || line ipred2 age || /* */
line ipred3 age
```

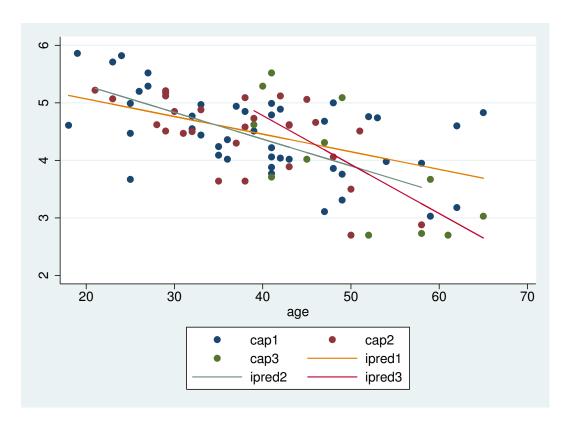


Figure 6: . scatter cap1 cap2 cap3 age —— line ipred1 age —— line ipred2 age —— /*

. graph export graph6.eps replace (file graph6.eps written in EPS format)

2.6 The least steep is in the baseline (least exposed group) The steepest is in the most exposed group

. lincom age + 3.exposure#c.age
(1) age + 3.exposure#c.age = 0

capacity Coef. Std. Err. t P>|t| [95% Conf. Interval]

(1) -.085111 .0196716 -4.33 0.000 -.1242742 -.0459478

. use \$datadir/hald, clear

. sw regress y x1 x2 x3 x4, pe(0.05)

begin with empty model

p = 0.0006 < 0.0500 adding x4 p = 0.0000 < 0.0500 adding x1

1		0						
Source	SS	df		MS		Number of obs	=	13
						F(2, 10)	=	176.63
Model	2641.00094	2	1320	.50047		Prob > F	=	0.0000
Residual	74.7621108	10	7.47	7621108		R-squared	=	0.9725
						Adj R-squared	=	0.9670
Total	2715.76305	12	226	.313587		Root MSE	=	2.7343
	Q s	Q+ 1	F		D. I.I.	[OF% G 6	T	
у	Coef.	Std.	Err.	t	P> t	[95% Conf.	In.	terval
x4	6139536	.0486	3446	-12.62	0.000	7223404	_	5055668
x1	1.439958	.1384		10.40	0.000	1.131547		1.74837
_cons	103.0974	2.123	984	48.54	0.000	98.36485	1	07.8299

3.1 x1 & x4 are retained

. sw regress y x1 x2 x3 x4, pr(0.05) begin with full model

p = 0.8959 >= 0.0500 removing x3 p = 0.2054 >= 0.0500 removing x4

	Source	SS	df		MS		Number of obs	=	13
_							F(2, 10)	=	229.50
	Model	2657.85857	2	1328	.92929		Prob > F	=	0.0000
	Residual	57.9044793	10	5.79	044793		R-squared	=	0.9787
_							Adj R-squared	=	0.9744
	Total	2715.76305	12	226.	313587		Root MSE	=	2.4063
_									
	у	Coef.	Std.	Err.	t	P> t	[95% Conf.	In	terval]
_	x1	1.468306	.1213	3009	12.10	0.000	1.19803	1	.738581
	x2	.6622505	.0458	3547	14.44	0.000	.5600798		7644212
	_cons	52.57735	2.286	3174	23.00	0.000	47.48344	5	7.67126

3.2 This time x1 & x2 are retained

. sw regress y x1 x2 x3 x4, pe(0.05) pr(0.0500005) begin with full model

p = 0.8959 >= 0.0500 removing x3 p = 0.2054 >= 0.0500 removing x4

Source	SS	df	MS		Number of obs	
Model Residual	2657.85857 57.9044793	2 10	1328.92929 5.79044793		F(2, 10) Prob > F R-squared	= 0.0000 = 0.9787
Total	2715.76305	12	226.313587		Adj R-squared Root MSE	= 0.9744 = 2.4063
у	Coef.	Std. 1	Err. t	P> t	[95% Conf.	Interval]
x1 x2 _cons	1.468306 .6622505 52.57735	.12130 .0458! 2.286	547 14.44	0.000	1.19803 .5600798 47.48344	1.738581 .7644212 57.67126

3.3 This is the same as the backwards model

. corr x* (obs=13)

	x1	x2	х3	x4
x1 x2 x3 x4		1.0000 -0.1392 -0.9730	1.0000 0.0295	1.0000

3.4 Correlation between x2 & x4 is -0.97

 $3.5~\mathrm{x2}$ & x4 are very strongly correlated: they contain the same information, so they are largely interchangeable

. regress y x1 x2 x3 x4

Source	SS	df	MS		Number of obs	
Model Residual	2667.89941 47.863637	4 8	666.9748 5.982954	-	Prob > F R-squared	= 0.0000 = 0.9824
Total	2715.76305	12	226.3135	37	Adj R-squared Root MSE	= 2.446
у	Coef.	Std.	Err.	t P> t	[95% Conf.	Interval]
x1 x2 x3	1.551103 .5101677 .1019096	.74476 .723	788 0	.08 0.071 .70 0.501 .14 0.896	1663395 -1.15889 -1.638453	3.268545 2.179226 1.842272
x4 _cons	1440609 62.40535	.7090 70.070		.20 0.844 .89 0.399	-1.779138 -99.17856	1.491016 223.9893

3.6 The F statistic says that the model is very highly significant: the null hypothesis that all coefficients are 0 could not have given rise to this data

3.7 98% of the variance is explained

3.8 None of the coefficients are significant, due to the strong correlations between them

- . use \$datadir/growth, clear
- . scatter weight week

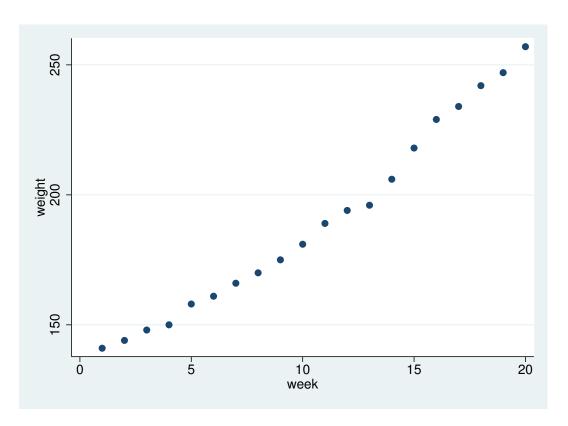


Figure 7: . scatter weight week

. graph export graph7.eps replace (file graph7.eps written in EPS format)

4.1 The line does not look quite straight: there appears to be some curvature

. regress weight week

Source	SS	df		MS		Number of obs = 20
Model Residual	25438.7504 579.449624	1 18	25438.7504 32.1916458			F(1, 18) = 790.23 Prob > F = 0.0000 R-squared = 0.9777
Total	26018.2	19	1369	.37895		Adj R-squared = 0.9765 Root MSE = 5.6738
weight	Coef.	Std.	Err.	t	P> t	[95% Conf. Interval]
week _cons	6.184962 125.3579	.2200 2.635		28.11 47.56	0.000	5.722719 6.647206 119.8206 130.8952

- . cprplot week
 - 4.2 There is definitely curvature around the line
- . gen week2 = week * week
- . regress weight week week2

Source	SS	df		MS		Number of obs = 20
Model Residual	25927.7513 90.4487127	2 17		3.8756 051251		F(2, 17) = 2436.58 Prob > F = 0.0000 R-squared = 0.9965
Total	26018.2	19	1369	.37895		Adj R-squared = 0.9961 Root MSE = 2.3066
weight	Coef.	Std.	Err.	t	P> t	[95% Conf. Interval]
week week2 _cons	2.680178 .1668945 138.2088	.3763 .0174 1.716	086	7.12 9.59 80.54	0.000 0.000 0.000	1.886119 3.474237 .1301656 .2036235 134.5881 141.8294

- 4.3 week2 is very highly significant (p = 0.000)
- . predict pred2, xb
- . twoway scatter weight week $\mid \mid$ line pred2 week
- . graph export graph8.eps replace (file graph8.eps written in EPS format)
 - 4.4 Curved predictor fits the data very well

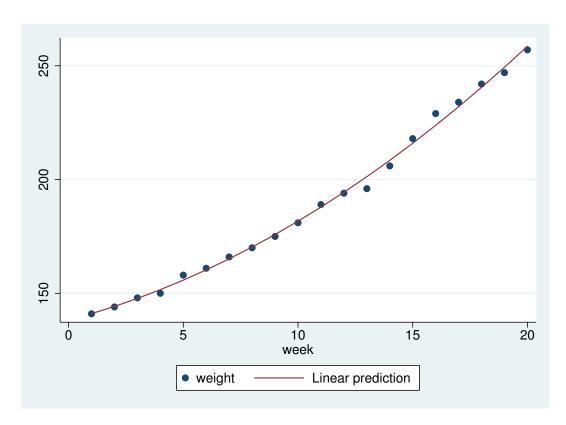


Figure 8: . twoway scatter weight week —— line pred2 week

. gen week3 = week2*week

. regress weight week week2 week3 $\,$

Source	SS	df	MS		Number of obs F(3, 16)	
Model Residual	25928.9007 89.2992705		642.96691 5.58120441		Prob > F R-squared	= 0.0000 = 0.9966
Total	26018.2	19 1	369.37895		Adj R-squared Root MSE	= 0.9959 = 2.3625
weight	Coef.	Std. Er	r. t	P> t	[95% Conf.	Interval]
week week2 week3 _cons	2.242641 .2177334 0016139 139.0663	1.03833 .113435 .003556 2.58058	33 1.92 34 -0.45	0.073 0.656	.0414737 0227388 0091531 133.5957	4.443808 .4582055 .0059252 144.5369

4.5 week3 is not significant

. corr week* (obs=20)

	week	week2	week3
week week2 week3	1.0000 0.9713 0.9221	1.0000 0.9865	1.0000

4.6 Correlation between week and week2 is 0.97 end of do-file $\,$