

**Sociology 593**  
**Exam 1 Answer Key**  
**February 11, 2005**

I. *True-False.* (20 points) Indicate whether the following statements are true or false. If false, briefly explain why.

1. A researcher is trying to construct a scale that measures political liberalism. She obtains the following results:

`. alpha lib*, c i`

`Test scale = mean(unstandardized items)`

Item	Obs	Sign	item-test correlation	item-rest correlation	average inter-item covariance	alpha
liberal1	3975	+	0.8436	0.3092	.0592051	0.5014
liberal2	3975	+	0.5812	0.4236	.0544034	0.7169
liberal3	3975	+	0.5262	0.3809	.0575775	0.7238
liberal4	3975	+	0.5010	0.3260	.0578235	0.7337
liberal5	3975	+	0.6197	0.4707	.0527308	0.7086
liberal6	3975	+	0.6542	0.5158	.0513626	0.7007
liberal7	3975	+	0.5306	0.3668	.0567058	0.7264
liberal8	3975	+	0.6010	0.4630	.0543518	0.7108
liberal9	3975	+	0.3012	0.5006	.0515661	0.8392
Test scale					.0550807	0.7459

Based on these results, if she wants to increase the reliability of her scale, she should drop liberal1.

False. The last column shows you what the Cronbach's Alpha would be if the item was deleted. Thus, if you dropped liberal1, the reliability of the scale would go down, from .7459 to .5014. If she wants to increase the reliability of the scale she should drop liberal9.

2.  $sr_1^2 = .23$ ,  $sr_2^2 = .15$ . Therefore, dropping both  $x_1$  and  $x_2$  from the equation will reduce  $R^2$  by .38.

False (unless  $x_1$  and  $x_2$  are uncorrelated). Semipartial correlations have to be recomputed after each variable is dropped.

3. In a bivariate regression, random measurement error in  $X$  causes the slope coefficient to be attenuated. Unfortunately, increasing the sample size will not alleviate this problem.

True. A larger sample size will not affect the attenuation bias that is caused by random measurement error.

4. Religion is coded 1 = Catholic, 2 = Protestant, 3 = Other. However, information on religion is missing for several respondents. According to Allison and others, the best way to deal with this problem is to treat missing as another category of religion and then construct 3 dummy variables from religion.

False. As pointed out in the notes on missing data, Allison says that this procedure will produce biased estimates.

5. Outlying values on Y will have the greatest influence on regression coefficients when (a) their corresponding X values are close to the mean of X, and (b) the Y value is out of line with the rest of the Y values, i.e. it does not fall on the same line that the other cases do.

False (or only half-true). Part (b) is right, but for (a) outliers on Y that are paired with average values of X will have less influence on parameter estimates than outliers on Y that are paired with above or below-average values on X. Influence on coefficients = Leverage \* Discrepancy, and cases that are further from the mean of X have greater leverage.

II. *Short answer.* Discuss three of the following five problems. (15 points each, 45 points total, up to 5 points extra credit for each additional problem.) In each case, the researcher has used Stata to test for a possible problem, concluded that there is a problem, and then adopted a strategy to address that problem. Explain (a) what problem the researcher was testing for, and why she concluded that there was a problem, (b) the rationale behind the solution she chose, i.e. how does it try to address the problem, and (c) one alternative solution she could have tried, and why. (NOTE: a few sentences on each point will probably suffice – you don't have to repeat everything that was in the lecture notes.)

II-1.

```
. reg y x
```

Source	SS	df	MS	Number of obs =	80
Model	8161.29461	1	8161.29461	F( 1, 78) =	0.64
Residual	987754.387	78	12663.5178	Prob > F =	0.4245
				R-squared =	0.0082
				Adj R-squared =	-0.0045
Total	995915.682	79	12606.5276	Root MSE =	112.53

y	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
x	-2.032806	2.532175	-0.80	0.425	-7.073978 3.008366
_cons	-12.75283	12.58149	-1.01	0.314	-37.80066 12.295

```
. predict rstudent, rstudent
. predict cooksd, cooksd
. extremes rstudent cooksd y x
```

obs:	rstudent	cooksd	y	x
75.	-188.0042	1.870291	-999	8.116624
1.	-.3794509	.0082487	-26.45146	-13.27932
2.	-.2554911	.0021359	-20.94568	-9.759867
10.	-.1944049	.0005867	-22.56966	-5.837373
3.	-.1862795	.000874	-16.46544	-8.301276

76.	.4368796	.0052328	17.54447	8.773149
77.	.4445563	.0059247	17.25927	9.270648
78.	.4700404	.0067283	19.84505	9.361078
74.	.4758831	.0050422	24.34256	7.662218
80.	.511474	.0102893	20.86036	10.86633

```
. preserve
. drop if y == -999
(1 observation deleted)

. * [CONTINUED NEXT PAGE]
```

```
. reg y x
```

Source	SS	df	MS	Number of obs = 79		
Model	8772.60996	1	8772.60996	F( 1, 77)	=	314.60
Residual	2147.13658	77	27.8848907	Prob > F	=	0.0000
Total	10919.7465	78	139.996751	R-squared	=	0.8034
				Adj R-squared	=	0.8008
				Root MSE	=	5.2806

  

y	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
x	2.144088	.1208823	17.74	0.000	1.903381	2.384795
_cons	-.0483975	.5942454	-0.08	0.935	-1.231691	1.134896

```
. restore
```

The researcher is concerned about outliers. The studentized residual measures discrepancy while the Cook statistic measures influence. By listing extreme values, the researcher finds that the residual statistics for case 75 are enormously large and that the y value for that case is -999. The researcher opts to simply drop the outlying case from the analysis. Notice that the regression coefficients change dramatically when she does this. This is a reasonable strategy if -999 is a known data error or is supposed to be a missing data code. Possibly better would be to double-check the coding to make sure the wrong number wasn't entered. If, by some chance, -999 is a legitimate code, the researcher may want to look for additional explanatory variables, or try a technique like `qreg` or `rreg` that is designed to deal with outliers.

//2.

```
. reg y x
```

Source	SS	df	MS	Number of obs = 240		
Model	2611.95343	1	2611.95343	F( 1, 238)	=	14.98
Residual	41486.6545	238	174.313674	Prob > F	=	0.0001
Total	44098.6079	239	184.513004	R-squared	=	0.0592
				Adj R-squared	=	0.0553
				Root MSE	=	13.203

  

y	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
x	1.148551	.2967106	3.87	0.000	.5640361	1.733065
_cons	-.3421508	1.841041	-0.19	0.853	-3.968968	3.284666

```
. hettest
```

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity

Ho: Constant variance

Variables: fitted values of y

chi2(1) = 81.80

Prob > chi2 = 0.0000

```
. reg y x, robust
```

Regression with robust standard errors

Number of obs = 240  
F( 1, 238) = 13.00  
Prob > F = 0.0004  
R-squared = 0.0592  
Root MSE = 13.203

y	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x	1.148551	.3185281	3.61	0.000	.521056	1.776045
_cons	-.3421508	1.224297	-0.28	0.780	-2.753993	2.069692

The researcher is concerned that errors are heteroscedastic, and the significant value for the Breusch-Pagan test suggests that this is indeed the case. To address the problem, she opts to use robust standard errors, which relax the assumption that errors are independent and identically distributed. This makes the standard errors more accurate but does not change the parameter estimates themselves. The use of robust standard errors has a very modest effect in this case, changing the estimates of the standard errors only slightly. Another alternative would be to try weighted least squares, if she thinks she knows enough to specify what the weights are. Transformations of the variables might also be warranted in some cases, e.g. take logs; or, the heteroscedasticity might go away if additional variables were added to the model or if subgroups were analyzed separately.

//3.

```
. reg activism ses liberalism black white
```

Source	SS	df	MS	Number of obs =	400
Model	27155.3953	4	6788.84883	F( 4, 395) =	589.72
Residual	4547.19637	395	11.5118895	Prob > F =	0.0000
Total	31702.5917	399	79.455117	R-squared =	0.8566
				Adj R-squared =	0.8551
				Root MSE =	3.3929

activism	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
ses	1.756392	.0488747	35.94	0.000	1.660305	1.852479
liberalism	.6095345	.0363666	16.76	0.000	.5380382	.6810308
black	1.420534	.6593005	2.15	0.032	.1243567	2.71671
white	5.159183	.569313	9.06	0.000	4.039921	6.278446
_cons	-7.413753	1.019549	-7.27	0.000	-9.418173	-5.409332

```
. sum
```

Variable	Obs	Mean	Std. Dev.	Min	Max
activism	500	27.79	8.973491	5	48.3
ses	400	12.96	3.961393	2	21
liberalism	500	13.52	5.061703	1	21
black	500	.2	.4004006	0	1
other	500	.1	.3003005	0	1
white	500	.7	.4587165	0	1
race	500	1.4	.6639893	1	3

```
. impute ses liberalism black white, gen(xses)
20.00% (100) observations imputed
```

```
. sum ses xses
```

Variable	Obs	Mean	Std. Dev.	Min	Max
ses	400	12.96	3.961393	2	21
xses	500	13.04019	3.627564	2	21

```
. reg activism xses liberalism black white
```

Source	SS	df	MS	Number of obs =	500
Model	29226.966	4	7306.7415	F( 4, 495) =	330.18
Residual	10954.2833	495	22.1298652	Prob > F =	0.0000
				R-squared =	0.7274
				Adj R-squared =	0.7252
Total	40181.2493	499	80.5235456	Root MSE =	4.7042

activism	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
xses	1.756392	.0677641	25.92	0.000	1.623251 1.889533
liberalism	.6381163	.04471	14.27	0.000	.5502715 .7259611
black	1.901355	.8433631	2.25	0.025	.244342 3.558368
white	5.155422	.7217568	7.14	0.000	3.737337 6.573507
_cons	-7.730077	1.342503	-5.76	0.000	-10.36778 -5.09237

The researcher was perhaps surprised that only 400 cases showed up in the regression analysis. A look at the summary statistics revealed that 100 cases were missing on ses. The researcher opted to replace those missing values with regression estimates. That is, by using the `impute` command, for the 400 cases where data was not missing, ses was regressed on liberalism, black and white. The resulting regression coefficients were then used to compute estimates of ses for the other 100 cases. The researcher apparently believes that the regression estimates are the “best guess” as to the values of the missing cases, but there are various problems with this strategy. The significance tests will not reflect the uncertainty that is created by using estimates rather than real values for some cases. The impute approach assumes that the 100 missing cases are typical; they may be missing precisely because they are not typical and a regression estimate may therefore be a bad estimate. Assuming you can’t find out what the true values for the missing cases are, sticking with listwise deletion, or using more advanced techniques, like multiple imputation, may be better. You need to know why the data are missing to decide on the best strategy.

//4.

**. reg y x1 x2 x3**

Source	SS	df	MS	Number of obs =	142
Model	2487.49068	3	829.163558	F( 3, 138) =	4.14
Residual	27620.5083	138	200.148611	Prob > F =	0.0076
Total	30107.999	141	213.531908	R-squared =	0.0826
				Adj R-squared =	0.0627
				Root MSE =	14.147

  

y	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
x1	-1.264819	1.710862	-0.74	0.461	-4.647712 2.118074
x2	.4646403	1.195707	0.39	0.698	-1.899635 2.828915
x3	1.547936	1.196244	1.29	0.198	-.817401 3.913273
_cons	20.29428	1.376812	14.74	0.000	17.5719 23.01666

**. test x1=x2=x3**

( 1) x1 - x2 = 0  
( 2) x1 - x3 = 0

F( 2, 138) = 0.60  
Prob > F = 0.5504

**. alpha x1 x2 x3, c i gen(xscale)**

Test scale = mean(unstandardized items)

Item	Obs	Sign	item-test correlation	item-rest correlation	average inter-item covariance	alpha
x1	142	+	0.9958	0.9907	26.42669	0.9816
x2	142	+	0.9898	0.9770	26.46523	0.9907
x3	142	+	0.9900	0.9773	26.26876	0.9906
Test scale					26.38689	0.9917

**. reg y xscale**

Source	SS	df	MS	Number of obs =	142
Model	2247.45567	1	2247.45567	F( 1, 140) =	11.29
Residual	27860.5433	140	199.003881	Prob > F =	0.0010
Total	30107.999	141	213.531908	R-squared =	0.0746
				Adj R-squared =	0.0680
				Root MSE =	14.107

  

y	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
xscale	.773987	.2303132	3.36	0.001	.3186454 1.229329
_cons	20.21559	1.370705	14.75	0.000	17.50563 22.92555

The researcher is concerned about multicollinearity. The Global F is significant but the individual T values are not. The researcher apparently thinks that it may be legitimate to combine the 3 Xs into a single scale. The test command shows that indeed, their effects do not significantly differ from each other (hence they can be added together) and the alpha command further shows that, if added together, they would form a highly

reliable scale. Once she creates the scale, the problem of multicollinearity obviously goes away. Incidentally, note that, although  $R^2$  declines when she does this, adjusted  $R^2$  goes up, which seems to further validate her decision. Even though this seems to work, simply adding the items together could be a questionable choice if they are measured in very different ways. Other options could include dropping some of the variables (but this could lead to specification error) or just using an incremental F test for all 3 X coefficients together rather than separate T tests.

//5.

```
. reg activism anomia1 anomia2 anomia3 anomia4 anomia5
```

Source	SS	df	MS	Number of obs = 3975		
Model	14532.664	5	2906.5328	F( 5, 3969)	=	29.11
Residual	396311.025	3969	99.8516062	Prob > F	=	0.0000
				R-squared	=	0.0354
				Adj R-squared	=	0.0342
				Root MSE	=	9.9926
Total	410843.689	3974	103.382911			

  

activism	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
anomia1	4.374225	3.002524	1.46	0.145	-1.512409	10.26086
anomia2	-1.658814	1.585215	-1.05	0.295	-4.766726	1.449098
anomia3	-2.497017	1.585327	-1.58	0.115	-5.605148	.6111143
anomia4	1.868915	1.129336	1.65	0.098	-.3452169	4.083047
anomia5	1.932719	1.58515	1.22	0.223	-1.175066	5.040504
_cons	-.0062429	.1910416	-0.03	0.974	-.3807918	.3683061

```
. corr
```

(obs=3975)

	anomia1	anomia2	anomia3	anomia4	anomia5	activism
anomia1	1.0000					
anomia2	0.9776	1.0000				
anomia3	0.9775	0.9556	1.0000			
anomia4	0.9571	0.9353	0.9345	1.0000		
anomia5	0.9774	0.9555	0.9554	0.9354	1.0000	
activism	0.1829	0.1753	0.1735	0.1827	0.1828	1.0000

```
. sw reg activism anomia1 anomia2 anomia3 anomia4 anomia5, pe(.05)
```

begin with empty model  
p = 0.0000 < 0.0500 adding anomia1

Source	SS	df	MS	Number of obs = 3975		
Model	13744.2243	1	13744.2243	F( 1, 3973)	=	137.51
Residual	397099.465	3973	99.9495254	Prob > F	=	0.0000
				R-squared	=	0.0335
				Adj R-squared	=	0.0332
				Root MSE	=	9.9975
Total	410843.689	3974	103.382911			

  

activism	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
anomia1	4.014533	.342346	11.73	0.000	3.343342	4.685723
_cons	-.0045298	.1911315	-0.02	0.981	-.3792549	.3701952

Once again, the researcher is concerned about multicollinearity. Again, the Global F is significant and the individual T values are not; further the correlation matrix shows that the anomia measures are very highly correlated with each other. However, rather than use the brain that God gave him to try to find a solution for the problem, he uses mindless atheoretical stepwise regression to pick the variables. Stepwise regression chooses the variables that will most increase  $R^2$ , i.e. it just uses blind empiricism to select the variables for the model. This is potentially problematic. Note that anomia1 just barely edges out the other measures; a slightly different sample could easily produce different results. This could also result in specification error if one or more of the other variables is supposed to be in the model. If it is believed that the items all measure exactly the same thing and are more or less interchangeable, then it might make more sense for the researcher to choose whichever item he feels has the most face validity. Constructing a scale from the anomia items might be another good choice.

### III. Computation and interpretation. (35 points total)

President Bush realizes that he faces a tough battle in getting the American people to back his plan for reforming Social Security. He wants to know what factors currently affect support for his plan. His pollsters have collected data from 3000 individuals on the following variables:

Variable	Description
ssplan	Support for Bush's plan, measured on a scale that ranges from 0 (strongly opposes plan) to 100 (strongly supports plan).
bush	Coded 1 if the respondent voted for Bush in 2004, 0 otherwise
female	Coded 1 if the respondent is female, 0 otherwise
age	Age in years

The study obtains the following results.

**. corr, means**

(obs=3000)

Variable	Mean	Std. Dev.	Min	Max
ssplan	54.95611	18.35886	5.713294	97.19326
bush	.5166667	.4998055	0	1
female	.5333333	.4989708	0	1
age	47.15	14.16359	13.08336	82.43011

  

	ssplan	bush	female	age
ssplan	1.0000			
bush	0.7023	1.0000		
female	-0.1564	-0.1025	1.0000	
age	-0.1319	0.1359	0.0814	1.0000



. reg ssplan bush female age, beta

Source	SS	df	MS	Number of obs =	3000
Model	555765.846	3	185255.282	F( 3, 2996) =	1219.73
Residual	455039.916	2996	151.882482	Prob > F =	0.0000
Total	1010805.76	2999	337.047603	R-squared =	<b>[1]</b>
				Root MSE =	12.324

  

ssplan	Coef.	Std. Err.	t	P> t	Beta
bush	26.68239	.4575126	58.32	0.000	.726407
female	-2.338038	.4555404	<b>[2]</b>	0.000	-.0635449
age	-.292231	.0161132	-18.14	0.000	<b>[3]</b>
_cons	56.19586	.8172954	68.76	0.000	.

. vif

Variable	VIF	1/VIF
bush	<b>[4]</b>	0.968552
age	1.03	0.972347
female	1.02	0.980228
Mean VIF	1.03	

. test bush

( 1) bush = 0

F( 1, 2996) = **[5]**  
 Prob > F = 0.0000

. test bush = female

( 1) bush - female = 0

F( 1, 2996) = 2283.01  
 Prob > F = 0.0000

. test female age

( 1) female = 0

( 2) age = 0

F( 2, 2996) = 188.40  
 Prob > F = 0.0000

```
. pcorr2 ssplan bush female age
```

```
(obs=3000)
```

Partial and Semipartial correlations of ssplan with

Variable	Partial	SemiP	Partial^2	SemiP^2	Sig.
bush	0.7292	0.7149	0.5317	0.5111	0.000
female	-0.0934	-0.0629	0.0087	0.0040	0.000
age	-0.3145	-0.2223	0.0989	0.0494	0.000

```
. hettest age
```

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity

Ho: Constant variance

Variables: age

chi2(1) = 0.75

Prob > chi2 = 0.3872

a) (10 pts) Fill in the missing quantities [1] – [5].

Here are the uncensored parts of the printout:

```
. reg ssplan bush female age, beta
```

Source	SS	df	MS	Number of obs = 3000	
Model	555765.846	3	185255.282	F( 3, 2996) = 1219.73	
Residual	455039.916	2996	151.882482	Prob > F = 0.0000	
Total	1010805.76	2999	337.047603	R-squared = 0.5498	
				Adj R-squared = 0.5494	
				Root MSE = 12.324	

  

ssplan	Coef.	Std. Err.	t	P> t	Beta
bush	26.68239	.4575126	58.32	0.000	.726407
female	-2.338038	.4555404	-5.13	0.000	-.0635449
age	-.292231	.0161132	-18.14	0.000	-.2254519
_cons	56.19586	.8172954	68.76	0.000	.

. vif

Variable	VIF	1/VIF
bush	1.03	0.968552
age	1.03	0.972347
female	1.02	0.980228
Mean VIF	1.03	

. test bush

( 1) bush = 0

F( 1, 2996) = 3401.29  
Prob > F = 0.0000

To confirm that Stata got it right:

$$[1] = R^2 = SSR/SST = 555765.846/1010805.76 = .5498$$

$$[2] = t_{\text{female}} = b_{\text{female}} / s_{b\text{-female}} = -2.338038 / .4555404 = -5.13$$

$$[3] = b'_{\text{age}} = b_{\text{age}} * s_{\text{age}} / s_{\text{ssplan}} = -.292231 * 14.16359 / 18.35886 = -.2254519$$

$$[4] = vif_{\text{bush}} = 1/Tol_{\text{bush}} = 1/ 0.968552 = 1.03$$

$$[5] = \text{Wald test of } (H_0: \beta_{\text{bush}} = 0) = T_{\text{bush}}^2 = 58.32^2 = 3401.22$$

b) (20 points) Interpret the results. Be sure to answer the following questions, explaining how the printout supports your conclusions.

1. What percentage of the sample is female? What percentage voted for Bush?

As you can see from the means in the descriptive statistics, 53.33% of the sample is female (i.e. 1600 people), while 51.67% voted for Bush (i.e. 1550 people).

2. Who was more likely to have voted for Bush – men or women? Younger people or older people?

The correlation matrix shows that female is negatively correlated with bush, which means that women were less likely to vote for Bush. On the other hand, age is positively correlated with Bush, which means that older people were more likely to vote for him than were younger people.

3. Which variable has the strongest impact on support for Bush's plan? Cite at least two pieces of evidence from the printout to support your conclusion on this point.

The variable bush (voted for Bush) has the largest T value, the largest standardized beta, and the largest partial and semipartial correlations. Hence, voting for Bush seems to be the strongest determinant of supporting Bush's social security plan. Of course, the direction of the causality may be debateable here; perhaps people voted for Bush at least partly because they supported his social security plan.

4. According to the model, which types of individuals are most likely to support Bush's plan?

The signs of the regression coefficients imply that people who voted for Bush, men, and younger individuals are more likely to support his social security plan.

5. Bush's statistical advisors were worried that there would be heteroscedasticity associated with age, i.e. the older the respondents were, the more variability there would be in their responses. Were these fears warranted?

The chi-square value of the `hettest` for age is insignificant, suggesting that this fear was not borne out by the data.

- c) (5 points) The advisor preparing the report for Bush is very annoyed with his assistant who did the computer runs. He specifically told her that he wanted to be able to do an incremental F test of the hypothesis that neither age nor gender affected support for Bush's plan; but since only one model was estimated, he says he cannot do that. Explain why you either agree or disagree with him; if you disagree, give him the information he wants.

Perhaps the advisor is so used to doing things with SPSS that he does not realize that Stata has an equivalent way of doing things. The command `test female age` does a Wald test of the hypothesis that neither age nor gender affects support for Bush's plan; the highly significant F value indicates that this hypothesis should be rejected, i.e. one or the other or both affects support. In the case of OLS regression, the Wald test and the incremental F test will yield identical results (although this need not be true for other techniques like logistic regression.) To confirm this we will use the `hireg` command to compute the incremental F value for us and then repeat the Wald test presented earlier:

```
. hireg ssplan (bush) (female age), nomiss
```

```
[UNNECESSARY PARTS OF OUTPUT DELETED]...
```

Model	R2	F(df)	p	R2 change	F(df) change	p
1:	0.493	2917.627(1,2998)	0.000			
2:	0.550	1219.728(3,2996)	0.000	0.057	188.401(2,2996)	0.000

```
. test female age
```

```
( 1) female = 0  
( 2) age = 0
```

```
F( 2, 2996) = 188.40  
Prob > F = 0.0000
```

As you see, both the Wald test and the incremental F test produce a highly significant F value of 188.40.