Homework #8

A. Shawn Bandy

May 1, 2013

1 Lab Problems

STATA log:

name: <unnamed>

log: /Users/shawn/src/econ485/lab8/lab8.log

log type: text

opened on: 1 May 2013, 19:46:55

- . /*a. Use OLS regression to estimate the following model.
- > i. Dependent variable: approve, this indicates the person had their loan
- > approved; explanatory variables are hrat loanprc unem_ind male married dep school cosign chist bankrupt m
- > late1 mortlate2 high_vacancy white

- > regress approve hrat loanprc unem_ind male married dep school cosign chist bankrupt mortlate1 mortlate2 h > _vacancy white;

Source	SS	df	MS	Number of obs =	1129
+				F(14, 1114) =	13.02
Model	17.4548957	14	1.24677826	Prob > F = 0	0.0000
Residual	106.685051	1114	.09576755	R-squared =	0.1406
+				Adj R-squared = 0	0.1298
Total	124.139947	1128	.110053144	Root MSE =	.30946

approve	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
hrat	002343	.0012929	-1.81	0.070	0048798	.0001939
loanprc	2308079	.050282	-4.59	0.000	3294659	1321499
unem_ind	0092055	.0042917	-2.14	0.032	0176262	0007848
male	0018928	.025833	-0.07	0.942	0525795	.0487939
married	.0270134	.022177	1.22	0.223	0165	.0705268
dep	0012066	.008995	-0.13	0.893	0188556	.0164425
school	.0235984	.02298	1.03	0.305	0214905	.0686874
cosign	.0430834	.0570779	0.75	0.451	0689089	.1550757

```
chist | .0778704 .0266316 2.92 0.004
                                                .0256165
                                                          .1301242
   bankrupt | -.2775626 .0401785 -6.91 0.000
                                                 -.3563966 -.1987286
  mortlate1 | -.1231576 .0622179 -1.98 0.048
                                               -.2452351
                                                            -.00108
                       .0911409 -1.25 0.213
  mortlate2 | -.1135754
                                                 -.2924027
                                                            .0652518
high_vacancy | -.0312386
                                  -1.64 0.102
                       .0190719
                                                 -.0686595
                                                            .0061824
                                                .0791617
                                  4.97 0.000
     white | .1307452
                        .02629
                                                            .1823286
             .9709887
      _cons |
                        .0696573
                                  13.94 0.000
                                                 .8343144
                                                            1.107663
```

. outreg2 using l1a, excel;

l1a.xml
dir : seeout

- . /*b. Use logit to estimate the following model.
- > i. Dependent variable: approve, this indicates the person had their loan
- > approved; explanatory variables are hrat loanprc unem_ind male married dep school cosign chist bankrupt m
- > late1 mortlate2 high_vacancy white*/

>

> logit approve hrat loanprc unem_ind male married dep school cosign chist bankrupt mortlate1 mortlate2 hig > acancy white;

Iteration 0: log likelihood = -427.07309
Iteration 1: log likelihood = -375.10341
Iteration 2: log likelihood = -359.21725
Iteration 3: log likelihood = -358.84609
Iteration 4: log likelihood = -358.84587
Iteration 5: log likelihood = -358.84587

Logistic regression Number of obs = 1129 LR chi2(14) = 136.45 Prob > chi2 = 0.0000 Log likelihood = -358.84587 Pseudo R2 = 0.1598

approve	 +-	Coef.	Std. Err.	z	P> z	[95% Conf.	Interval]
hrat	i I	0275274	.0130925	-2.10	0.036	0531883	0018665
loanprc		-2.658952	.5933799	-4.48	0.000	-3.821955	-1.495949
unem_ind		0798995	.0409675	-1.95	0.051	1601944	.0003955
male		0227519	.2654709	-0.09	0.932	5430653	.4975615
married		.3085338	.2288233	1.35	0.178	1399516	.7570192
dep		.0063583	.09827	0.06	0.948	1862473	. 1989638
school		.2104498	.2291448	0.92	0.358	2386657	.6595653
cosign		.5403811	.6952712	0.78	0.437	8223255	1.903088
chist		.7160148	.2357092	3.04	0.002	.2540334	1.177996
bankrupt		-1.577179	.2959106	-5.33	0.000	-2.157153	9972051
mortlate1		9114942	.516367	-1.77	0.078	-1.923555	.1005666
mortlate2		-1.006185	.7677763	-1.31	0.190	-2.510999	.4986289
high_vacancy		3248466	.1997244	-1.63	0.104	7162992	.0666061

```
      white | .980196 .2207503
      4.44 0.000 .5475335
      1.412859

      _cons | 3.823727 .7364631
      5.19 0.000 2.380286
      5.267169
```

. /*c. Estimate the marginal effects of each variable using the mean value of all dependent variables using

>

Conditional marginal effects Number of obs = 1129

Model VCE : OIM

Expression : Pr(approve), predict()

white | .0814474

dy/dx w.r.t. : hrat loanprc unem_ind male married dep school cosign chist bankrupt mortlate1 mortlate2

high_vacancy white

: hrat at 24.99965 (mean) loanprc .7770578 (mean) 3.933127 (mean) unem_ind male .8193091 (mean) .6651904 (mean) married dep = .789194 (mean) = school .7767936 (mean) cosign = .0274579 (mean) = .8467671 (mean) chist = .0602303 (mean) bankrupt mortlate1 = .0230292 (mean) mortlate2 = .0106289 (mean) = .4136404 (mean) high_vacancy .8423384 (mean) white

1 Delta-method dy/dx Std. Err. z P>|z| [95% Conf. Interval] hrat | -.0022873 .0010783 -2.12 0.034 -.0044008 -.0001739 loanprc | -.2209402 .0475649 -4.65 0.000 -.3141657 -.1277147 unem_ind | -.0066391 .0033977 -1.95 0.051 -.0132984 male | -.0018905 .0220579 -0.09 0.932 -.0451232 .0413421 married | .025637 .0189388 1.35 0.176 -.0114823 .0627563 dep | .0005283 .0081643 0.06 0.948 -.0154735 .0165302 school | .0174869 .0190367 0.92 0.358 -.0198244 .0547982 0.78 0.436 cosign | .0449019 .0576884 -.0681653 . 157969 .0214917 3.07 0.002 chist | .0594958 .0193902 .0974998 bankrupt | -.1310525 .0257742 -5.08 0.000 -.181569 -.080536 mortlate1 | -.0757387 .0429695 -1.76 0.078 -.1599574 .0084799 mortlate2 | -.0836069 .0637277 -1.31 0.190 -.2085109 .0412971 high_vacancy | -.0269925 .0165356 -1.63 0.103 -.0594016 .0054167

4.44 0.000

.0454645

.1174303

.018359

> rgins and atmeans.*/

> margins, dydx(hrat loanprc unem_ind male married dep school cosign chist bankrupt mortlate1 mortlate2 his > vacancy white) atmean;

. /*d. Estimate the marginal effects of each variable as the average of the marginal effects using margins > margins, dydx(hrat loanprc unem_ind male married dep school cosign chist bankrupt mortlate1 mortlate2 has

> vacancy white);

Average marginal effects Number of obs = 1129

Model VCE : OIM

Expression : Pr(approve), predict()

dy/dx w.r.t. : hrat loanprc unem_ind male married dep school cosign chist bankrupt mortlate1 mortlate2

high_vacancy white

	dy/dx	Delta-method Std. Err.	i z	P> z	[95% Conf	. Interval]
hrat	0025541	.0012134	-2.10	0.035	0049324	0001758
loanprc	2467099	.0546889	-4.51	0.000	3538982	1395217
unem_ind	0074134	.0037948	-1.95	0.051	0148511	.0000242
male	002111	.024632	-0.09	0.932	0503888	.0461667
married	.0286272	.0212268	1.35	0.177	0129767	.0702311
dep	.0005899	.0091183	0.06	0.948	0172816	.0184615
school	.0195265	.0212501	0.92	0.358	022123	.061176
cosign	.0501391	.0644924	0.78	0.437	0762637	.1765418
chist	.0664352	.021798	3.05	0.002	.0237119	.1091585
bankrupt	146338	.0264733	-5.53	0.000	1982248	0944513
mortlate1	0845727	.0477961	-1.77	0.077	1782514	.009106
mortlate2	0933585	.0711689	-1.31	0.190	232847	.0461299
high_vacancy	0301408	.018512	-1.63	0.103	0664236	.006142
white	.0909471	.0202593	4.49	0.000	.0512396	.1306547

^{. /*}e. Since male is a discrete dummy variable, use margins and male = $(0\ 1)$ to get the marginal effects.*/
> margins, at(white = $(0\ 1)$);

Predictive margins Number of obs = 1129

Model VCE : OIM

2._at

Expression : Pr(approve), predict()

: white

1._at : white = 0

| Delta-method | Margin Std. Err. z P>|z| [95% Conf. Interval]

1

```
_at |
1 | .7853829 .0274062 28.66 0.000 .7316676 .8390981
2 | .8962455 .0096968 92.43 0.000 .87724 .9152509
```

. /*f. Use probit to estimate the following model.

> probit approve hrat loanprc unem_ind male married dep school cosign chist bankrupt mortlate1 mortlate2 his > vacancy white;

Iteration 0: log likelihood = -427.07309
Iteration 1: log likelihood = -360.21513
Iteration 2: log likelihood = -358.10227
Iteration 3: log likelihood = -358.09673
Iteration 4: log likelihood = -358.09673

Probit regression Number of obs = 1129 LR chi2(14) = 137.95 Prob > chi2 = 0.0000 Log likelihood = -358.09673 Pseudo R2 = 0.1615

approve		Coef.	Std. Err.	z	P> z	[95% Conf.	Interval]
hrat	i	0135664	.0068335	-1.99	0.047	0269598	000173
loanprc	1	-1.472842	.3234929	-4.55	0.000	-2.106877	8388076
unem_ind	1	0436724	.022401	-1.95	0.051	0875775	.0002328
male		0022475	.1418946	-0.02	0.987	2803558	.2758607
married	1	.1596008	.1218806	1.31	0.190	0792807	.3984824
dep	1	0005295	.0518209	-0.01	0.992	1020967	.1010377
school	1	.1059921	.1251761	0.85	0.397	1393485	.3513328
cosign		.2868798	.3672053	0.78	0.435	4328294	1.006589
chist		.3824942	.1328699	2.88	0.004	.122074	.6429144
bankrupt	1	9169555	.1734877	-5.29	0.000	-1.256985	576926
mortlate1	1	5067942	.2896844	-1.75	0.080	-1.074565	.0609768
mortlate2		5938387	.4167723	-1.42	0.154	-1.410697	.22302
high_vacancy		1970612	.1060091	-1.86	0.063	4048351	.0107128
white	1	.537414	.1246858	4.31	0.000	.2930342	.7817937
_cons	1	2.154494	.3974403	5.42	0.000	1.375525	2.933463

^{. /*}g. Estimate the marginal effects from using probit of each variable as the average of the

> i. Dependent variable: approve, this indicates the person had their loan

> approved; explanatory variables are hrat loanprc unem_ind male married dep school cosign chist bankrupt m

> late1 mortlate2 high_vacancy white*/

> marginal effects using margins.*/

>

> margins, dydx(hrat loanprc unem_ind male married dep school cosign chist bankrupt mortlate1 mortlate2 his > vacancy white);

Average marginal effects Number of obs = 1129

Model VCE : OIM

Expression : Pr(approve), predict()

dy/dx w.r.t. : hrat loanprc unem_ind male married dep school cosign chist bankrupt mortlate1 mortlate2

high_vacancy white

			Delta-method				
	1	dy/dx	Std. Err.	z	P> z	[95% Conf.	<pre>Interval]</pre>
	+-						
hrat		0023444	.0011809	-1.99	0.047	0046589	0000298
loanprc		2545185	.055422	-4.59	0.000	3631436	1458934
unem_ind		0075469	.0038648	-1.95	0.051	0151217	.0000279
male		0003884	.0245206	-0.02	0.987	0484478	.0476711
married		.0275803	.0210582	1.31	0.190	0136931	.0688536
dep		0000915	.008955	-0.01	0.992	017643	.01746
school		.0183163	.0216291	0.85	0.397	0240759	.0607084
cosign		.049575	.0634456	0.78	0.435	0747761	.1739261
chist		.066098	.0229046	2.89	0.004	.0212057	.1109902
bankrupt	1	158457	.0292084	-5.43	0.000	2157045	1012095
mortlate1	1	087578	.0499713	-1.75	0.080	1855198	.0103639
mortlate2		1026199	.0719063	-1.43	0.154	2435536	.0383138
high_vacancy		0340537	.0182738	-1.86	0.062	0698696	.0017622
white	1	.0928693	.0213516	4.35	0.000	.051021	. 1347176

. log close;

name: <unnamed>

log: /Users/shawn/src/econ485/lab8/lab8.log

log type: text

closed on: 1 May 2013, 19:46:57

2 Questions

- Q1 Use the results from L1 to answer this question.
 - a. Assuming you dont have any violations of OLS, interpret the coefficient on white from the regression you ran in L1, part a).

Being white as opposed to being black increases the probability of being approved for a loan by about 13%, all other things held constant.

b. Use the following values and the coefficients from L1, part a). What is the estimated probability? Hint: Only use statistically significant coefficients with p-values less than 0.10.

The estimated probability is 0.9128844.

c. What is a potential problem with using the model you estimated in L1, part a)?

It was possible for the estimated probability to not be in the interval [0..1].

d. Use your results from the model you estimated in L1, part b). Does there appear to be a positive or negative impact on the probability of getting a loan from being white relative to being black?

Being white appears to have a positive impact on the probability of getting a loan.

e. Use your marginal results from L1, part c). Interpret the marginal effect for the variable white.

Being white increases the probability of being approved for a loan by about 8.14 percent. These are for the mean value of 'white' in the sample but 'white' is a dummy variable that can only take the values of 0 or 1.

f. Use your marginal results from L1, part d). Interpret the marginal effect for the variable white.

Being white increases the probability of being approved for a loan by 9.09 percent.

g. Are the marginal results from parts e) and f) above the same? Explain why there might be a difference, even if it is small.

No, they differ by about 0.85 percent. In L1.d we are taking the calculating the partial effects for each observation and taking the mean whereas in L1.c we are taking the average values of the observations and then calculating the partial effect.

h. Use your results from L1, part e). Calculate the difference between the two estimates. This is the marginal difference between being white and being nonwhite. Compare your answer to your answer in part g).

noop (Although I ran it with white and got a difference of about 0.1108626.)

i. Use your results from the model you estimated in L1, part f). Does there appear to be a positive or negative impact on the probability of getting a loan from being white relative to being black?

There appears to be a positive impact on the probability of getting a loan from being white.

j. Multiply the coefficient from L1 part f) on white by 1.81. How does this compare to the coefficient on white in L1 part b)? Explain.

0.537414 * 1.81 = 0.97271934

I do not see any comparison (it is close to the constant in my regression from part b) so I have obviously missed something.

k. Use your results from L1, part g). Interpret the marginal effect for the variable white.

Being white increases the probability of being approved for a loan by about 9.29 percent.

- l. Compare the marginal effect for the variable white as discussed in this question in parts f) and k). The answers for the partial effect of white on the probability of being approved for a loan are very close about .20 precent different.
- m. Based on these results, does there appear to be a racial bias in terms of who gets loans approved?

Based on these result, there certainly appears to be a racial bias in terms of who gets loans approved.

¹I am assuming that we are being asked about the above answer in part k and not this answer which is part l.