

Assignment 3

1. Estimate the model assuming that the probability function is (a) cumulative normal probability distribution function and (b) logistic probability distribution function. Interpret your estimated result (overall test, individual test, pseudo R2, counted R2).

a) Probit model

```
. probit y x1 x2 x3 x4
```

```
Iteration 0:  log likelihood = -248.43455
Iteration 1:  log likelihood = -150.03919
Iteration 2:  log likelihood = -147.48531
Iteration 3:  log likelihood = -147.46882
Iteration 4:  log likelihood = -147.46881
```

```
Probit regression               Number of obs   =       400
                               LR chi2(4)           =       201.93
                               Prob > chi2           =       0.0000
Log likelihood = -147.46881     Pseudo R2        =       0.4064
```

y	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
x1	.3590739	.0371539	9.66	0.000	.2862536	.4318941
x2	-.8525746	.144481	-5.90	0.000	-1.135752	-.569397
x3	-.5735764	.2202882	-2.60	0.009	-1.005333	-.1418195
x4	-1.248569	.226762	-5.51	0.000	-1.693014	-.8041238
_cons	1.45664	.2037279	7.15	0.000	1.057341	1.85594

```
. fitstat
```

Measures of Fit for probit of y

Log-Lik Intercept Only:	-248.435	Log-Lik Full Model:	-147.469
D(395):	294.938	LR(4):	201.931
		Prob > LR:	0.000
McFadden's R2:	0.406	McFadden's Adj R2:	0.386
Maximum Likelihood R2:	0.396	Cragg & Uhler's R2:	0.557
McKelvey and Zavoina's R2:	0.640	Efron's R2:	0.446
Variance of y*:	2.775	Variance of error:	1.000
Count R2:	0.818	Adj Count R2:	0.416
AIC:	0.762	AIC*n:	304.938
BIC:	-2071.691	BIC':	-177.966

b) Logistic model

```
. logit y x1 x2 x3 x4
```

```
Iteration 0:  log likelihood = -248.43455
Iteration 1:  log likelihood = -154.06753
Iteration 2:  log likelihood = -148.00091
Iteration 3:  log likelihood = -147.90887
Iteration 4:  log likelihood = -147.90869
Iteration 5:  log likelihood = -147.90869
```

```
Logistic regression              Number of obs   =       400
                                LR chi2(4)         =       201.05
                                Prob > chi2          =       0.0000
Log likelihood = -147.90869      Pseudo R2        =       0.4046
```

y	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
x1	.6299401	.0708979	8.89	0.000	.4909828	.7688974
x2	-1.488248	.2597744	-5.73	0.000	-1.997396	-.9790992
x3	-.9562902	.3882611	-2.46	0.014	-1.717268	-.1953124
x4	-2.155321	.4055058	-5.32	0.000	-2.950097	-1.360544
_cons	2.5165	.3714373	6.78	0.000	1.788496	3.244503

```
. fitstat
```

Measures of Fit for logit of y

Log-Lik Intercept Only:	-248.435	Log-Lik Full Model:	-147.909
D(395):	295.817	LR(4):	201.052
		Prob > LR:	0.000
McFadden's R2:	0.405	McFadden's Adj R2:	0.385
Maximum Likelihood R2:	0.395	Cragg & Uhler's R2:	0.555
McKelvey and Zavoina's R2:	0.622	Efron's R2:	0.445
Variance of y*:	8.707	Variance of error:	3.290
Count R2:	0.818	Adj Count R2:	0.416
AIC:	0.765	AIC*n:	305.817
BIC:	-2070.811	BIC':	-177.086

The overall LR-test for both models are statistically significant since Prob>chi equals to 0. For the individual test, all independent variables in both models are statistically significant at 95% confidence level since p-values of each variable are less than 0.05. In addition, pseudo R² for probit and logistic models are 0.406 and 0.405, respectively, meaning that independent variables in each model can explain the model by 40.6% and 40.5%. Lastly, counted R² implies how much the model can correctly predict the outcome. In this case, counted R² of models are equal to 81.8% which is higher than 50%. Then, this model can properly use.

2. Make a comparison of the goodness of fit of the two models.

To consider the goodness of fit of the two models, we need to compare the Pseudo R² of two models. In this case, the probit model seems to have a better fit to the data compared with the Logistic model since the Pseudo R² is a bit higher (0.406>0.405).

3. From the Probit model, show how to compute Overall LR-test.

From the above result, Overall LR-test = 2(LogUR - LogR) = 2((-147.469)-(-248.435)) = 201.932

4 From the Logit model, compute the predicted value of index value and predicted probability of being a bad loan by using the mean value of all Xs.

```
. mfx, predict(xb)
```

Marginal effects after logit

```
y = Linear prediction (log odds) (predict, xb)
= 1.32418
```

variable	dy/dx	Std. Err.	z	P> z	[	95% C.I.	]	X
x1	.6299401	.0709	8.89	0.000	.490983	.768897		.454973
x2	-1.488248	.25977	-5.73	0.000	-1.9974	-.979099		.809344
x3	-.9562902	.38826	-2.46	0.014	-1.71727	-.195312		.556712
x4	-2.155321	.40551	-5.32	0.000	-2.9501	-1.36054		-.119684

$$\hat{I} = \square_0 + \square_1 \bar{x}_1 + \square_2 \bar{x}_2 + \square_3 \bar{x}_3 + \square_4 \bar{x}_4 = 2.52 + 0.63 \cdot 0.45 - 1.49 \cdot 0.81 - 0.96 \cdot 0.81 - 2.16 \cdot (-0.12) = 1.0782$$

5. Compute marginal effect at mean and at the median for Logit model.

The marginal effect of each variable at mean and median can be seen in x column.

```
. mfx
```

Marginal effects after logit

```
y = Pr(y) (predict)
= .7898763
```

variable	dy/dx	Std. Err.	z	P> z	[	95% C.I.	]	X
x1	.1045522	.01146	9.12	0.000	.082083	.127022		.454973
x2	-.247007	.04388	-5.63	0.000	-.333011	-.161003		.809344
x3	-.1587171	.06397	-2.48	0.013	-.2841	-.033334		.556712
x4	-.3577223	.06679	-5.36	0.000	-.488633	-.226812		-.119684

```
. mfx, at(median)
```

Marginal effects after logit

```
y = Pr(y) (predict)
= .84127022
```

variable	dy/dx	Std. Err.	z	P> z	[	95% C.I.	]	X
x1	.0841188	.00961	8.76	0.000	.065292	.102946		.655749
x2	-.1987326	.03349	-5.93	0.000	-.264373	-.133093		.692745
x3	-.1276979	.04944	-2.58	0.010	-.224597	-.030799		.488768
x4	-.28781	.05616	-5.12	0.000	-.397881	-.177739		-.109732

6. Compute marginal effect at the value of $X_1=0.5$, $X_2=1$, $X_3=0.5$, $X_4=0$ for the Probit model.

```
. mfx, at(0.5 1 0.5 0)
```

Marginal effects after probit

```
y = Pr(y) (predict)
= .69034
```

variable	dy/dx	Std. Err.	z	P> z	[	95% C.I.	]	X
x1	.1266183	.01307	9.69	0.000	.101001	.152235		.5
x2	-.3006389	.05452	-5.51	0.000	-.4075	-.193778		1
x3	-.2022572	.07644	-2.65	0.008	-.352085	-.05243		.5
x4	-.4402764	.08419	-5.23	0.000	-.605293	-.27526		0

7. Determine counted R^2 using the threshold of predicted value = 0.5 for Logit models.

```
. estat clas
```

Logistic model for y

Classified	True		Total
	D	~D	
+	251	49	300
-	24	76	100
Total	275	125	400

Classified + if predicted $\Pr(D) \geq .5$

True D defined as $y \neq 0$

Sensitivity	$\Pr(+ D)$	91.27%
Specificity	$\Pr(- \sim D)$	60.80%
Positive predictive value	$\Pr(D +)$	83.67%
Negative predictive value	$\Pr(\sim D -)$	76.00%
False + rate for true ~D	$\Pr(+ \sim D)$	39.20%
False - rate for true D	$\Pr(- D)$	8.73%
False + rate for classified +	$\Pr(\sim D +)$	16.33%
False - rate for classified -	$\Pr(D -)$	24.00%
Correctly classified		81.75%


```
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```

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AIC:	0.765	AIC*n:	305.817
BIC:	-2070.811	BIC':	-177.086

The counted R^2 of the logit model is 81.75%.

8. Determine counted R^2 using the threshold of predicted value = 0.7 for Logit models.

```
. estat clas, cut(0.7)
```

Logistic model for y

Classified	True		Total
	D	~D	
+	217	24	241
-	58	101	159
Total	275	125	400

Classified + if predicted $\Pr(D) \geq .7$

True D defined as $y \neq 0$

Sensitivity	$\Pr(+ D)$	78.91%
Specificity	$\Pr(- \sim D)$	80.80%
Positive predictive value	$\Pr(D +)$	90.04%
Negative predictive value	$\Pr(\sim D -)$	63.52%
False + rate for true ~D	$\Pr(+ \sim D)$	19.20%
False - rate for true D	$\Pr(- D)$	21.09%
False + rate for classified +	$\Pr(\sim D +)$	9.96%
False - rate for classified -	$\Pr(D -)$	36.48%
Correctly classified		79.50%

The counted R^2 of the logit model using 0.7 of threshold of predicted value is 79.5%.