

Assignment 3

1.

a)

```
. probit y x1 x2 x3 x4
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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)

```
. 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

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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

According to the MLE regression model, the overall test using LR chi-square test of probit model and logit model are slightly different at 201.93 for probit model and 201.05 for logit model, and both are significant (H_0 is rejected, $P\text{-value} : 0.0000 < 0.05$). For the Pseudo R^2 and counted R^2 , there are no different between 2 models ; Pseudo $R^2 = 0.4046$ and Counted $R^2 = 0.818$. And all X_s are significant where $P\text{-values}$ are $0.0000 < 0.05$, H_0 is rejected. X_s are relevant in the model.

2.

From the above fitstat result, it is seen that Pseudo (McFadden) R^2 of the probit model has a higher value at 0.406, while that of the logit model has a lower value of fit at 0.405. Hence, the probit model is better than the logit model.

3.

$$\text{Overall LR-test} = 2 [\log L_{UR} - \log L_R] \sim \chi^2(k-1)$$

$$\text{Overall LR-test} = 2 [-147.469 - (-248.435)]$$

$$= 201.932 \#$$

4.

```

. mfx, predict(xb)

Marginal effects after logit
y = Linear prediction (log odds) (predict, xb)
I = 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	


```

. mfx

Marginal effects after logit
y = Pr(y) (predict)
P = .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	

$$\hat{I} = x\hat{\beta}$$

$$= 2.5765 + 0.629(0.45) + (-1.48)(0.809)$$

$$+ (-0.956)(0.556) + (-2.155)(-0.119)$$

$$\hat{I} = 1.32 \#$$

$$\hat{P} = \frac{1}{1 + e^{-\hat{I}}}$$

$$= \frac{1}{1 + e^{-1.32}}$$

$$= 0.789 \#$$

$\hat{P} = 1/1 + e^{-\hat{I}}$, $\hat{P} = 0.7898$. Since $\hat{P} > 0.5$, $Y_i = 1$
The firm has a bad loan.

$$\hat{P} < 0.5 \rightarrow Y = 0$$

$$\hat{P} > 0.5 \rightarrow Y = 1$$

5.

$$mfx : \hat{p}(1-\hat{p})\hat{\beta}$$

```
. mfx at mean
Marginal effects after logit
y = Pr(y) (predict)
p-hat = .7898763
variable | dy/dx | Std. Err. | z | P>|z| | [ 95% C.I. ] | X
```

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)
p-hat = .84127022
variable | dy/dx | Std. Err. | z | P>|z| | [ 95% C.I. ] | X
```

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

$$0.789(1-0.789)(0.629)$$

$$\hat{p} \text{ at mean} = 0.789$$

$$\hat{p} \text{ at median} = 0.841$$

6.

$$x_1 x_2 x_3 x_4$$

```
. mfx, at(0.5 1 0.5 0)
Marginal effects after probit
y = Pr(y) (predict)
p-hat = .69034
variable | dy/dx | Std. Err. | z | P>|z| | [ 95% C.I. ] | X
```

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.

```
. 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) >= .5
True D defined as y != 0
```

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

$$\text{counted } R^2 = \frac{76 + 251}{400} = 0.8175$$

8.

```
. 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) >= .7
True D defined as y != 0

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

$$\text{Counted } R^2 = \frac{107 + 277}{400} = 0.795$$