

a.)

. 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
 Pseudo R2 = 0.4064

Log likelihood = -147.46881

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

$p < \alpha = 0.05$, jointly significant in overall test.

Pseudo $R^2 = 0.4064$

all individual test are significant at .05 level

. 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

counted $R^2 = 0.818 > 0.5$ but Adj Counted $R^2 = 0.416 < 0.5$, so the model

is not accurately predicted y. Just guess would be better.

. 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
 Pseudo R2 = 0.4046

Log likelihood = -147.90869

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

overall test $\Rightarrow p > \alpha = 0.05$, jointly significant at .05 level.

Pseudo $R^2 = 0.4046$

. 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

All significant at .05 level of significance.

Pseudo R^2 of probit is higher than of logit model which is better.

counted $R^2 = 0.818 > 0.5$ but Adj Counted $R^2 = 0.416 < 0.5$, so the model

is not accurately predicted y.

b.)

Probit model has higher log-likelihood value and Pseudo R^2 , but

both models are not different in terms of goodness of fit.

c.)

```
. 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

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

$$= 2 [-149.969 + 248.435]$$

$$= 201.93$$

```
. probit y, nolog
```

```
Probit regression              Number of obs   =       400
                              LR chi2(0)         =        0.00
                              Prob > chi2         =        .
Log likelihood = -248.43455    Pseudo R2       =       0.0000
```

	y	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
	_cons	.4887764	.0654634	7.47	0.000	.3604706 .6170822

d.)

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

Marginal effects after logit

λ = Linear prediction (log odds) (predict, xb)
 $\lambda = 1.32418$

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

$\hat{p}$ = Pr(y) (predict)
 $\hat{p} = .7898763$

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

at mean

e.)

```
. 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	

at median

```
. 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	

f.)

```
. 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	-.193777	1	
x3	-.2022572	.07644	-2.65	0.008	-.352085	-.05243	.5	
x4	-.4402764	.08419	-5.23	0.000	-.605293	-.275259	0	

g.)

```
. predict pr
(option pr assumed; Pr(y))

. findit fitstat

. g yhat=0 if pr<=0.5
(300 missing values generated)

. replace yhat=1 if pr>0.5
(300 real changes made)

. 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	Overall	81.75%
----------------------	---------	--------

counted $R^2 = 0.8175$

```
. tabulate y yhat2
```

y	yhat2		Total
	0	1	
0	101	24	125
1	58	217	275
Total	159	241	400

$$\text{counted } R^2 = \frac{101 + 217}{400} = 0.795 \quad *$$