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. logit y x1 x2 x3 x4
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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
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Logistic regression      Number of obs   =      400
                        LR chi2(4)                =     201.05
                        Prob > chi2                 =     0.0000
Log likelihood = -147.90869  Pseudo R2       =     0.4046
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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

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. fitstat
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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
```

• Overall test

- LR-Chi square test equals to 201.05 with p value equals to 0.000
- It can be interpreted that all explanatory variable can use to explain dependent variable.

• Individual test

- All explanatory variable have p value less than 0.05
- It means that each of variable can use to explain dependent variable.

• pseudo R^2

- Pseudo R^2 equal to 0.405
- Lower pseudo R^2 than probit model. It mean that probit model has lower likelihood.

• counted R^2

- Model can explain outcome by 01.8%.

2. For comparing goodness of fit of two model, probit model is better than logit model since probit model has higher pseudo R^2 than logit model. Probit model can explain the data better than logit model.

4.

. 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

$$\hat{I} = 2.52 + 0.62(0.45) - 1.49(0.81) - 0.96(0.56) + 2.16(0.12)$$

$$= 1.32$$

5. . 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.

. mfx, at(0.5 1 0.5 0)

Marginal effects after logit
 y = Pr(y) (predict)
 = .70372027

variable	dy/dx	Std. Err.	z	P> z	[95% C.I.]	X
x1	.1313413	.01481	8.87	0.000	.102307	.160376		.5
x2	-.3102967	.0596	-5.21	0.000	-.427116	-.193478		1
x3	-.1993846	.07892	-2.53	0.012	-.354074	-.044695		.5
x4	-.4493802	.09126	-4.92	0.000	-.628243	-.270518		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%

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 $\Pr(D) \geq .7$
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%