

Example Logit Probit 2

The model

In the study of default probability of the loan, determination factors include:

$$Prob(Y=1|X) = f(X_1, X_2, X_3, X_4)$$

Dependent variable $Y_i = 1$ if the firm is bad loan, and $= 0$ for good loan.

Independent variables

X_1 is debt coverage ratio.

X_2 is liquidity ratio represented by current assets to current liabilities

X_3 is profitability ratio represented by sales to total assets

X_4 is solidity ratio represented by retained earnings to total assets

Requirements:

- 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 R^2 , counted R^2).
- 2 Make comparison of the goodness of fit of the two models.
- 3 From Probit model, show how to compute Overall LR-test.
- 4 From Logit model, compute predicted value of index value and predicted probability of being bad loan by using mean value of all X s.
- 5 Compute marginal effect at mean and at median for Logit model.
- 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.
- 7 Determine counted R^2 using the threshold of predicted value = 0.5 for Logit models.
- 8 Determine counted R^2 using the threshold of predicted value = 0.7 for Logit models.

- 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 R^2 , counted R^2).

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

```
Iteration 0: log likelihood = -265.87901
Iteration 1: log likelihood = -152.30041
Iteration 2: log likelihood = -147.75466
Iteration 3: log likelihood = -147.7109
Iteration 4: log likelihood = -147.71089
```

```
Probit regression
```

Number of obs	=	450
LR chi2(4)	=	236.34
Prob > chi2	=	0.0000
Pseudo R2	=	0.4444

Log likelihood = -147.71089

y	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
x1	.3636552	.036416	9.99	0.000	.2922811	.4350292
x2	-.862947	.1436001	-6.01	0.000	-1.144398	-.5814958
x3	-.5817432	.2191799	-2.65	0.008	-1.011328	-.1521586
x4	-1.262129	.2253211	-5.60	0.000	-1.70375	-.820508
_cons	1.474976	.2012109	7.33	0.000	1.08061	1.869342

```
. fitstat
```

Measures of Fit for probit of y

Log-Lik Intercept Only:	-265.879	Log-Lik Full Model:	-147.711
D(445):	295.422	LR(4):	236.336
		Prob > LR:	0.000
McFadden's R2:	0.444	McFadden's Adj R2:	0.426
ML (Cox-Snell) R2:	0.409	Cragg-Uhler(Nagelkerke) R2:	0.589
Mckelvey & Zavoina's R2:	0.669	Efron's R2:	0.472
Variance of y*:	3.021	Variance of error:	1.000
Count R2:	0.838	Adj Count R2:	0.416
AIC:	0.679	AIC*n:	305.422
BIC:	-2423.193	BIC':	-211.899
BIC used by Stata:	325.968	AIC used by Stata:	305.422

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

```
Iteration 0: log likelihood = -265.87901
Iteration 1: log likelihood = -159.64911
Iteration 2: log likelihood = -148.73788
Iteration 3: log likelihood = -148.40325
Iteration 4: log likelihood = -148.403
Iteration 5: log likelihood = -148.403
```

```
Logistic regression
```

Number of obs	=	450
LR chi2(4)	=	234.95
Prob > chi2	=	0.0000
Pseudo R2	=	0.4418

Log likelihood = -148.403

y	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
x1	.6431189	.0697691	9.22	0.000	.506374	.7798637
x2	-1.518271	.2591056	-5.86	0.000	-2.026108	-1.010433
x3	-.9789811	.3883357	-2.52	0.012	-1.740105	-.2178571
x4	-2.194103	.4045806	-5.42	0.000	-2.987067	-1.40114
_cons	2.568447	.3682716	6.97	0.000	1.846648	3.290246

```
. fitstat
```

Measures of Fit for logit of y

Log-Lik Intercept Only:	-265.879	Log-Lik Full Model:	-148.403
D(445):	296.806	LR(4):	234.952
		Prob > LR:	0.000
McFadden's R2:	0.442	McFadden's Adj R2:	0.423
ML (Cox-Snell) R2:	0.407	Cragg-Uhler(Nagelkerke) R2:	0.587
Mckelvey & Zavoina's R2:	0.656	Efron's R2:	0.471
Variance of y*:	9.559	Variance of error:	3.290
Count R2:	0.838	Adj Count R2:	0.416
AIC:	0.682	AIC*n:	306.806
BIC:	-2421.809	BIC':	-210.515
BIC used by Stata:	327.352	AIC used by Stata:	306.806

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

According to the above results, it seems that logit model provide a little bit better fitting the data compare to probit model since McFadden's R² from logit is a little bit higher than from probit (0.444>0.442).

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

From the above result LR-test = $2 \left((-147.711) - (-265.879) \right) = 236.336$

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

. mfx, predict(xb)

Marginal effects after logit
y = Linear prediction (log odds) (predict, xb)
= 1.7377664

variable	dy/dx	Std. Err.	z	P> z	[	95% C.I.	]	x
x1	.6431189	.06977	9.22	0.000	.506374	.779864	.897658	
x2	-1.518271	.25911	-5.86	0.000	-2.02611	-1.01043	.765019	
x3	-.9789811	.38834	-2.52	0.012	-1.74011	-.217857	.543069	
x4	-2.194103	.40458	-5.42	0.000	-2.98707	-1.40114	-.129975	

From the estimated result,

$$\hat{I} = -2.19 + 0.643(0.898) - 1.518(0.765) - 0.979(0.543) - 2.194(-0.13) = 1.738$$

$$\hat{P} = \frac{1}{1 + e^{-(1.738)}} = 0.8504$$

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

. mfx

Marginal effects after logit
y = Pr(y) (predict)
= .85040313

variable	dy/dx	Std. Err.	z	P> z	[	95% C.I.	]	x
x1	.0818161	.009	9.09	0.000	.064172	.099461	.897658	
x2	-.1931508	.03431	-5.63	0.000	-.260389	-.125912	.765019	
x3	-.1245437	.04894	-2.54	0.011	-.22046	-.028627	.543069	
x4	-.2791286	.05252	-5.31	0.000	-.382062	-.176195	-.129975	

. mfx, at(median)

Marginal effects after logit
y = Pr(y) (predict)
= .89138055

variable	dy/dx	Std. Err.	z	P> z	[	95% C.I.	]	x
x1	.0622676	.0079	7.88	0.000	.046777	.077758	1.04907	
x2	-.1470009	.02571	-5.72	0.000	-.1974	-.096602	.649129	
x3	-.0947862	.03605	-2.63	0.009	-.165443	-.024129	.482146	
x4	-.2124358	.04212	-5.04	0.000	-.294989	-.129883	-.145555	

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)
= .69251249
```

variable	dy/dx	Std. Err.	z	P> z	[95% C.I.]	x
x1	.1278389	.01294	9.88	0.000	.102481 .153196	.5
x2	-.3033593	.05437	-5.58	0.000	-.409922 -.196796	1
x3	-.2045053	.07588	-2.70	0.007	-.353228 -.055783	.5
x4	-.4436873	.08375	-5.30	0.000	-.60783 -.279544	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	
+	301	49	350
-	24	76	100
Total	325	125	450

```
Classified + if predicted Pr(D) >= .5
True D defined as y != 0
```

Sensitivity	Pr(+ D)	92.62%
Specificity	Pr(- ~D)	60.80%
Positive predictive value	Pr(D +)	86.00%
Negative predictive value	Pr(~D -)	76.00%
False + rate for true ~D	Pr(+ ~D)	39.20%
False - rate for true D	Pr(- D)	7.38%
False + rate for classified +	Pr(~D +)	14.00%
False - rate for classified -	Pr(D -)	24.00%
Correctly classified		83.78%

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	
+	267	24	291
-	58	101	159
Total	325	125	450

```
Classified + if predicted Pr(D) >= .7
True D defined as y != 0
```

Sensitivity	Pr(+ D)	82.15%
Specificity	Pr(- ~D)	80.80%
Positive predictive value	Pr(D +)	91.75%
Negative predictive value	Pr(~D -)	63.52%
False + rate for true ~D	Pr(+ ~D)	19.20%
False - rate for true D	Pr(- D)	17.85%
False + rate for classified +	Pr(~D +)	8.25%
False - rate for classified -	Pr(D -)	36.48%
Correctly classified		81.78%