

Binary Choice Model

After finish this session, you should understand:

- Concept of Logit/Probit model.
- Index Function, Latent variable, and Probability Model.
- Differences between Logit and Probit model.
- Interpretation of estimated results of Logit/Probit model
 - ① Sign & Meaning. (Nonlinear)
 - ② Overall Test. - LR χ^2 -test
 - ③ ~~R^2~~
 - ④ Ind. Test - z-test Asymp. Normal
- Marginal Effects
- Pseudo R-square vs Counted R-square

Example
STATA

$$Y = 0 \\ = 1$$

$$P(Y=1)$$

Logistic

Cum. Normal.

MLE

mpx

z-test

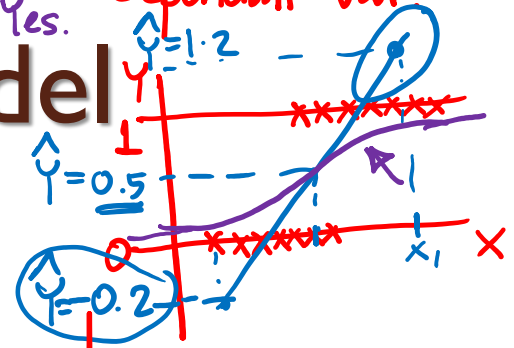
Asymp. Normal

Binary Choice Model

$Y = 0$ No
 $Y = 1$ Yes.
 Dummy Variable
 Dependent Var

Nonlinear

Concept of Choice Model



Discrete Choice Model

Decision making process:

Individual makes a marginal benefit-marginal cost calculation based on the utilities achieved by each choice.

Net benefit.

(+)

(-)

Model shows factors that influence decision making through the index function.

Index function determines net cost-benefit of each choice individual make.

Concept of Choice Model

Index function

$$\underline{U} = \underline{X}\underline{\beta} + \varepsilon$$

Latent Variable

Where U is unobserved variable of the difference between benefit and cost
 ε is normally or logistic distributed with mean 0 and variance 1

The observation is

$y = 1$ ✓	<i>if</i> $U > 0$
$y = 0$ ✓	<i>if</i> $U \leq 0$

Logit Model

Random Utility Models

$$U^a = \beta_{a1} + \beta_{a2}x_2 + \dots + \beta_{ak}x_k + \varepsilon_a \quad \text{and} \quad U^b = X\beta_b + \varepsilon_b$$

$Y=1$ if consumer's choice of alternative a : or b
 $Y=1$ $Y=0$

$$P_i = \Pr(y = 1 | X) = \Pr[U^a > U^b]$$

$$= \Pr[X\beta_a + \varepsilon_a - X\beta_b - \varepsilon_b > 0 | X]$$

$$= \Pr[X(\beta_a - \beta_b) + \varepsilon_a - \varepsilon_b > 0 | X]$$

$$P(Y=1|x) = \Pr[X\beta + \varepsilon > 0 | X]$$

Normal Distⁿ

Logit Model

$$Y = 0 \\ = 1$$

Index function

$$I_i = X\beta$$

$$P(Y=0) + P(Y=1) = 1$$

Assume that the probability function that the choice will be chosen is logistic distribution:

$$P_i = \Pr(y = 1 | X) = \frac{1}{1 + e^{-X\beta}}$$

$$P(Y=0|x) = 1 - \left(\frac{1}{1 + e^{x\beta}} \right)$$



if $\hat{P} \leq 0.5$
if $\hat{P} > 0.5$

$$P_i = \frac{1}{1 + e^{-X\beta}} = \frac{e^{X\beta}}{1 + e^{X\beta}} = \Lambda(X\beta)$$

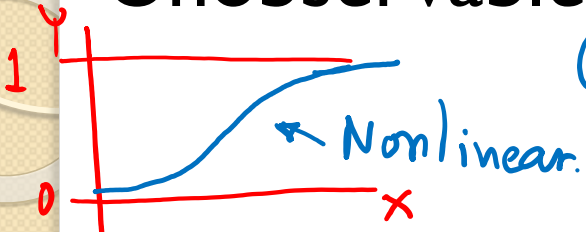
where: $\Lambda(\cdot)$ is logistic distribution function.

$P(1 \text{ or } 2 \text{ or } \dots \text{ or } n)$

$$L = \prod_{i=1}^n \left(\frac{1}{1 + e^{-X_i\beta}} \right)^{Y_i=1} \cdot \left(1 - \frac{1}{1 + e^{-X_i\beta}} \right)^{Y_i=0}$$

Probit Model

Unobservable utility index (I_i) or latent var.



① $I_i = X\beta$

$$\int_{-\infty}^{X\beta} \frac{1}{\sqrt{2\pi}\sigma^2} e^{-\frac{X\beta}{2\sigma^2}}$$

Assume I_i^* is threshold or critical level.

② $P_i = \Pr(y = 1 | X) = P(I_i^* \leq I_i) = F(X\beta) = \Phi(X\beta)$

Assume $\Phi(\cdot)$ is cumulative normal distribution function.

③ $\hat{y} = 0 \leftarrow \hat{p} \leq 0.5$
 $\hat{y} = 1 \leftarrow \hat{p} > 0.5$

MLE

$$L = \prod_{i=1}^n \Phi(\cdot)^{y_i=1} (1 - \Phi(\cdot))^{y_i=0}$$

Normit

- 1. Sign & Meaning mfx
- 2. Overall Test
- 3. R² 9
- 4. Ind. Test z-test

Marginal Effect

Logit Model

$$\frac{\partial \Pr(Y = 1|X)}{\partial X} = \Lambda(X\beta)$$

$$\frac{\partial \Pr(Y = 1|X)}{\partial x} = \Lambda(X\beta) [1 - \Lambda(X\beta)] \beta$$

$$= \hat{p} [1 - \hat{p}] \beta$$

Logistic

at Mean
at Median

mfx. at (value of X_0)

Mean
 \bar{X}

$$\frac{1}{1 + e^{-X\beta}}$$

Probit Model

$$\frac{\partial \Pr(Y = 1|X)}{\partial X} = \frac{\partial \Phi(X\beta)}{\partial X}$$

$$\frac{\partial \Pr(Y = 1|X)}{\partial x} = \phi(X\beta) \beta$$

Overall Significance Test

MLE

$$H_0: \underline{\beta}_2 = \underline{\beta}_3 = \dots = \underline{\beta}_k = \underline{0}$$

Test Statistic $2(\ln L_{UR} - \ln L_R) \sim \chi^2_{(k-1)}$

where LR χ^2 Test

$\ln L_{UR}$ = Log-likelihood value of estimated model

$\ln L_R$ = Log-likelihood value of restricted model

Individual Test — Z-test

Asymp. Normal.
 $n \rightarrow \infty$

Z-test: $H_0: \beta_i = 0$

Test Statistic Z-test = $\frac{\hat{\beta}_i}{\underline{s_{\hat{\beta}_i}}} \sim N(0,1)$

Measure Goodness of Fit

Pseudo (McFadden) R^2

$$\checkmark \text{McFadden } R^2 = 1 - \frac{\ln L_{UR}}{\ln L_R} < 1$$

where

$\ln L_{UR}$ = Log-likelihood value of estimated model

$\ln L_R$ = Log-likelihood value of restricted model
(model with only intercept term).

McFadden's Adjusted R^2

$$\text{McFadden's Adjusted } R^2 = 1 - \frac{\ln L_{UR} - k}{\ln L_R}$$

where k = Number of independent variables.

MLE

$$\log 0.1 = \begin{pmatrix} 1 \\ 2 \end{pmatrix}$$

$$\log 0.01 = \begin{pmatrix} 2 \\ 2 \end{pmatrix}$$

Make Comparison!

$$R^2 = 1 - \frac{RSS}{TSS}$$

$$R^2 = 0.9$$

Measure Goodness of Fit

~~X~~ Cox-Snell R^2

$$Cox - Snell R^2 = 1 - \exp\left(-2 \left[\ln L_{UR} - \ln L_R \right] / n\right)$$

~~X~~ Cox-Snell R^2 cannot attain a value of 1 which is the disadvantage of this measure. When the model perfectly fits, this $R^2=0.75$.

~~X~~ Cragg – Uhler (Nagelkerke) R^2

$$Cragg - Uhler R^2 = \frac{(Cox - Snell R^2)}{(1 - \exp(2[\ln L_R] / n))}$$

Measure Goodness of Fit

McKelvey – Zavoina R^2

$$\text{McKelvey – Zavoina } R^2 = \frac{\hat{\text{Var}}(\hat{I})}{\hat{\text{Var}}(\hat{I}) + \text{Var}(\hat{\varepsilon})}$$

where

$\hat{\text{Var}}(\hat{I})$ = variance of predicted index value

$\hat{\text{Var}}(\hat{\varepsilon})$ = variance of predicted residuals.

Measure Goodness of Fit

Efron R^2

$$\checkmark \text{ Efron } R^2 = 1 - \left(\frac{n}{n_1 \cdot n_2} \right) \sum_{i=1}^n (y_i - \hat{P}_i)^2$$

$(0 - 0.5)^2$
 $(1 - 0.9)^2$

where

Making Comparison

y_i = Actual value

$$n_1 + n_2 = n$$

\hat{P}_i = Predicted probability $Prob[y=1]$

$\checkmark n_1$ = Number of observation $y_i = 0$

$\checkmark n_2$ = Number of observation $y_i = 1$

n = Total number of observation.

Forecasting Error Index

Counted $R^2 > 0.5$

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

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

where

$$\text{Counted } R^2 = \frac{\text{No. of Correct Prediction}}{\text{Total No. of Observation}}$$

If $Prob[y=1]$ or $\hat{P} \leq 0.5$, then, $\hat{y} = 0$

If $Prob[y=1]$ or $\hat{P} > 0.5$, then, $\hat{y} = 1$

Actual

$Y=0$

$Y=1$

Example 1

$$\text{Counted } R^2 = \frac{90+3}{100} = 0.93 \text{ or } 93\%$$

	Predicted $Y=0$	Predicted $Y=1$	Total
Actual $Y=0$	✓ (90)	5 ✗	95
Actual $Y=1$	2 ✗	✓ (3)	5
Total	92	8	(100)

Forecasting Error Index

✓ Counted R²

Example 2

	$\uparrow=0$ Predicted Y=0	$\uparrow=1$ Predicted Y=1	Total
\rightarrow Actual Y=0	✓ (95)	0	(95) ✓
\rightarrow Actual Y=1	✗ 5	(0)	→ 5 ✓
Total	<u>100</u>	0 ←	(100) ✓

$$✓ \text{ Overall Counted } R^2 = \frac{95+0}{100} = 0.95 \text{ or } 95\%$$

$$✓ \text{ } \boxed{Y=0} \text{ Counted } R^2 = \frac{95}{95} = 1.00 \text{ or } 100\%$$

$$✓ \text{ } \boxed{Y=1} \text{ Counted } R^2 = \frac{0}{5} = 0.00 \text{ or } 0\%$$

Forecasting Error Index

Adjusted Counted R^2

$$\rightarrow \text{Counted } R^2 = \frac{\text{No. of Correct Prediction} - n^*}{\text{Total No. of Observation} - n^*}$$

where n^* is number of most frequent outcome.

Example 2


	Predicted $Y=0$	Predicted $Y=1$	Total
Actual $Y=0$	95	0	95 ✓
Actual $Y=1$	5	0	5
Total	100	0	100 ✓

$$\text{Overall Counted } R^2 = \frac{95 + 0}{100} = 0.95 \text{ or } 95\%$$

$$\rightarrow \text{Adjusted Counted } R^2 = \frac{(95 + 0) - 95}{100 - 95} = \frac{0}{5} = 0 \text{ or } 0\% \quad \times$$

Evaluation Criteria

$$\frac{\partial Y}{\partial X_2} = \beta_2$$

- ✓ 1. Sign and meaning of the Coefficients.
 - Whether the estimated results are according to the theory. (-) (+) $\frac{\partial P}{\partial X_2} \neq \beta_2$
 - Meaning – Marginal Effects at ...
- ✓ 2. Overall Test – LR-Chi-squares-test. MLE
 - Whether all explanatory variables can be used in explaining the dependent variable. $Y=0, 1$
- ✓ 3. GOF and Forecasting Error Index.
 - Pseudo R² - How well does the estimated results contribute to the likelihood of the model? – Making comparison
 - Counted R²
 - Overall $Y=0$ $Y=1$  > 0.5

Evaluation Criteria

- ✓ 4. Individual Test – z-test.
 - Whether each explanatory variables can explain the dependent variable.
 - z-test – MLE assume Asymptotic Normal.