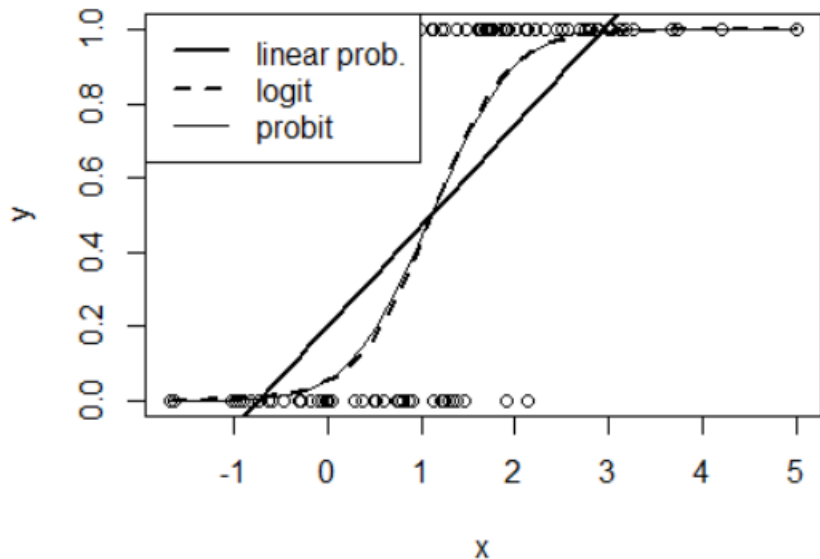


Logit and Probit

Vitor Kamada

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Specifying Logit and Probit Models

$$P(y = 1|x) = G(\beta_0 + x\beta)$$

$$0 < G(z) < 1$$

$$G(z) = \frac{e^z}{1+e^z} = \Lambda(z)$$

$$G(z) = \Phi(z) = \int_{-\infty}^z \phi(v) dv$$

$$\phi(v) = (2\pi)^{-\frac{1}{2}} \exp\left(-\frac{z^2}{2}\right)$$

$$y^* = \beta_0 + \mathbf{x}\beta + e$$

$$y = 1[y^* > 0]$$

$$e \perp \mathbf{x}$$

$$e \sim N(0, 1) \text{ or } \textit{Logistic}(0, 1)$$

$$\therefore 1 - G(-z) = G(z)$$

Maximum Likelihood Estimation (MLE)

$$f(y|x_i; \beta) = [G(x_i\beta)]^y [1 - G(x_i\beta)]^{1-y}$$

$$\ell_i(\beta) = y_i \log[G(x_i\beta)] + (1 - y_i) \log[1 - G(x_i\beta)]$$

$$\mathcal{L}(\beta) = \sum_{i=1}^n \ell_i(\beta)$$

Logistic Regression

$$\ell_i(\beta) = y_i \log[G(x_i\beta)] + (1 - y_i) \log[1 - G(x_i\beta)]$$

$$\frac{\partial \log \mathcal{L}(\beta)}{\partial \beta} = 0$$

$$\sum_{i=1}^n \left[\frac{y_i - G(x_i\beta)}{G(x_i\beta)(1 - G(x_i\beta))} g(x_i\beta) \right] x_i = 0$$

$$\sum_{i=1}^n \left[y_i - \frac{e^{x_i\beta}}{1 + e^{x_i\beta}} \right] x_i = 0$$

Response Probability for y

$$\begin{aligned}P(y = 1|x) &= P(y^* > 0|x) = P[e > -(\beta_0 + x\beta)|x] \\&= 1 - G[-(\beta_0 + x\beta)] = G(\beta_0 + x\beta)\end{aligned}$$

$$\frac{\partial p(x)}{\partial x_j} = g(\beta_0 + x\beta)\beta_j$$

$$g(z) = \frac{dG}{dz}(z) > 0$$

$G(\cdot)$ is a strictly increasing cdf

$$\phi(0) = \frac{1}{\sqrt{2\pi}} \approx .4, \quad \lambda(0) = \frac{\exp(0)}{[1+\exp(0)]^2} \approx .25$$

Partial Effect of Continuous Variables on the Response Probability

$$\frac{\partial p(x)}{\partial x_j} = g(\beta_0 + x\beta)\beta_j$$

$$\frac{\partial p(x)}{\partial x_j} / \frac{\partial p(x)}{\partial x_h} = \frac{\beta_j}{\beta_h}$$

Binary: $\frac{\Delta p(x)}{\Delta x_1} = G(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_k x_k)$

$$- G(\beta_0 + \beta_2 x_2 + \dots + \beta_k x_k)$$

Mroz (1987)

```
library(foreign);library(car); library(lmtest)  
mroz<-read.dta("C:/RData/mroz.dta")
```

Statistic	N	Mean	St. Dev.	Min	Max
inlf	753	0.568	0.496	0	1
kidslt6	753	0.238	0.524	0	3
kidsge6	753	1.353	1.320	0	8
age	753	42.538	8.073	30	60
educ	753	12.287	2.280	5	17
wage	428	4.178	3.310	0.128	25.000
nwifeinc	753	20.129	11.635	-0.029	96.000
lwage	428	1.190	0.723	-2.054	3.219

Linear Probability Model

```
linprob <- lm(inlf~nwifeinc+educ+exper+I(exper^2)+  
age+kidslt6+kidsge6, data=mroz)  
coeftest(linprob,vcov=hccm)
```

	Estimate	Std. Error	t value	Pr(> t)	
(Intercept)	0.58551922	0.15358032	3.8125	0.000149	***
nwifeinc	-0.00340517	0.00155826	-2.1852	0.029182	*
educ	0.03799530	0.00733982	5.1766	2.909e-07	***
exper	0.03949239	0.00598359	6.6001	7.800e-11	***
I(exper^2)	-0.00059631	0.00019895	-2.9973	0.002814	**
age	-0.01609081	0.00241459	-6.6640	5.183e-11	***
kidslt6	-0.26181047	0.03215160	-8.1430	1.621e-15	***
kidsge6	0.01301223	0.01366031	0.9526	0.341123	

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Logit Model

```
logitres<-glm(inlf~nwifeinc+educ+exper+I(exper^2)  
+age+kidslt6+kidsge6, family=binomial(link=logit),data=mroz)
```

	Estimate	Std. Error	z value	Pr(> z)	
(Intercept)	0.425452	0.860365	0.495	0.62095	
nwifeinc	-0.021345	0.008421	-2.535	0.01126	*
educ	0.221170	0.043439	5.091	3.55e-07	***
exper	0.205870	0.032057	6.422	1.34e-10	***
I(exper^2)	-0.003154	0.001016	-3.104	0.00191	**
age	-0.088024	0.014573	-6.040	1.54e-09	***
kidslt6	-1.443354	0.203583	-7.090	1.34e-12	***
kidsge6	0.060112	0.074789	0.804	0.42154	

Probit Model

```
probitres<-glm(inlf~nwifeinc+educ+exper+I(exper^2)+  
age+kidslt6+kidsge6, family=binomial(link=probit),data=mroz)
```

	Estimate	Std. Error	z	value	Pr(> z)	
(Intercept)	0.2700736	0.5080782	0.532	0.59503		
nwifeinc	-0.0120236	0.0049392	-2.434	0.01492	*	
educ	0.1309040	0.0253987	5.154	2.55e-07	***	
exper	0.1233472	0.0187587	6.575	4.85e-11	***	
I(exper^2)	-0.0018871	0.0005999	-3.145	0.00166	**	
age	-0.0528524	0.0084624	-6.246	4.22e-10	***	
kidslt6	-0.8683247	0.1183773	-7.335	2.21e-13	***	
kidsge6	0.0360056	0.0440303	0.818	0.41350		

$$\text{Pseudo } R^2 = 1 - \frac{\mathcal{L}_{ur}}{\mathcal{L}_0} = 1 - \frac{D_{ur}}{D_0}$$

\mathcal{L}_0 the model with only an intercept

$$|\mathcal{L}_{ur}| \leq |\mathcal{L}_0|$$

$$D = -2\mathcal{L}$$

`logLik(probitres)`

`—401.3022`

`1 - probitres$deviance/probitres$null.deviance`

`0.22`

Likelihood Ratio (LR) Test

$$LR = 2(\mathcal{L}_{ur} - \mathcal{L}_r)$$

$$LR \stackrel{a}{\sim} \chi_q^2$$

q # of exclusion restrictions

lrtest(restr,probitres)

```
Model 1: inlf ~ nwifeinc + educ + exper + I(exper^2) + age + kidslt6 + kidsge6
Model 2: inlf ~ 1
#Df  LogLik Df  Chisq Pr(>Chisq)
1    8 -401.30
2    1 -514.87 -7  227.14 < 2.2e-16 ***
```

```
restr <- glm(inlf~nwifeinc+educ+ kidslt6+kidsge6,
family=binomial(link=logit),data=mroz)
```

lrtest(restr,probitres)

```
Model 1: inlf ~ nwifeinc + educ + kidslt6 + kidsge6
Model 2: inlf ~ nwifeinc + educ + exper + I(exper^2) + age + kidslt6 + kidsge6
#Df  LogLik Df  Chisq Pr(>Chisq)
1    5 -464.92
2    8 -401.30  3 127.25 < 2.2e-16 ***
```


Partial Effect at the Average (PEA)

$$\Delta \hat{P}(y = 1|x) \approx [g(\hat{\beta}_0 + x\hat{\beta})\hat{\beta}_j]\Delta x_j$$

$$g(\hat{\beta}_0 + \bar{x}\hat{\beta}) = g(\hat{\beta}_0 + \hat{\beta}_1\bar{x}_1 + \hat{\beta}_2\bar{x}_2 + \dots + \hat{\beta}_k\bar{x}_k)$$

Partial Effect of x_j for the “average” person in the sample.

Marginal Effect at the Mean (MEM)

```
library(mfx)
```

```
logitmfx(inlf~nwifeinc+educ+exper+I(exper^2)  
+age+kidslt6+kidsge6, data=mroz, atmean=TRUE)
```

Marginal Effects:

	dF/dx	Std. Err.	z	P> z	
nwifeinc	-0.00519005	0.00204820	-2.5340	0.011278	*
educ	0.05377731	0.01056074	5.0922	3.539e-07	***
exper	0.05005693	0.00782462	6.3974	1.581e-10	***
I(exper^2)	-0.00076692	0.00024768	-3.0965	0.001959	**
age	-0.02140302	0.00353973	-6.0465	1.480e-09	***
kidslt6	-0.35094982	0.04963897	-7.0700	1.549e-12	***
kidsge6	0.01461621	0.01818832	0.8036	0.421625	

Average Partial Effect (APE) or Average Marginal Effect (AME)

$$n^{-1} \sum_{i=1}^n [g(\hat{\beta}_0 + x_i \hat{\beta}) \hat{\beta}_j]$$

AME is the average of the nonlinear function rather than the nonlinear function of the average

$$g[E(x\beta)] \neq E[g(x\beta)]$$

Average Marginal Effect (AME)

logitmfx(inlf~nwifeinc+educ+exper+I(exper^2)+age
+kidslt6+kidsge6, data=mroz, atmean=FALSE)

Marginal Effects:

	dF/dx	Std. Err.	z	P> z	
nwifeinc	-0.00381181	0.00153898	-2.4769	0.013255	*
educ	0.03949652	0.00846811	4.6641	3.099e-06	***
exper	0.03676411	0.00655577	5.6079	2.048e-08	***
I(exper^2)	-0.00056326	0.00018795	-2.9968	0.002728	**
age	-0.01571936	0.00293269	-5.3600	8.320e-08	***
kidslt6	-0.25775366	0.04263493	-6.0456	1.489e-09	***
kidsge6	0.01073482	0.01339130	0.8016	0.422769	

```
xpred <- list(nwifeinc=c(100,0),educ=c(5,17),exper=
c(0,30), age=c(20,52),kidslt6=c(2,0),kidsge6=c(0,0))
```

```
predict(linprob, xpred,type = "response")
```

1	2
-0.41	1.04

```
predict(logitres, xpred,type = "response")
```

1	2
0.005	0.95

```
predict(probitres,xpred,type = "response")
```

1	2
0.001	0.96