

## Regression Models for Binary Dependent Variables Using Stata, SAS, R, LIMDEP, and SPSS\*

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*This document summarizes logit and probit regression models for binary dependent variables and illustrates how to estimate individual models using Stata 11, SAS 9.2, R 2.9, LIMDEP 9, and SPSS 17.*

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## 1. Introduction

A categorical variable here refers to a variable that is binary, ordinal, or nominal. Event count data are discrete (categorical) but often treated as continuous variables. When a dependent variable is categorical, the ordinary least squares (OLS) method can no longer produce the best linear unbiased estimator (BLUE); that is, OLS is biased and inefficient. Consequently, researchers have developed various regression models for categorical dependent variables. The nonlinearity of categorical dependent variable models makes it difficult to fit the models and interpret their results.

### 1.1 Regression Models for Categorical Dependent Variables

In categorical dependent variable models, the left-hand side (LHS) variable or dependent variable is neither interval nor ratio, but rather categorical. The level of measurement and data generation process (DGP) of a dependent variable determine a proper model for data analysis. Binary responses (0 or 1) are modeled with binary logit and probit regressions, ordinal responses (1<sup>st</sup>, 2<sup>nd</sup>, 3<sup>rd</sup>, ...) are formulated into (generalized) ordinal logit/probit regressions, and nominal responses are analyzed by the multinomial logit (probit), conditional logit, or nested logit model depending on specific circumstances. Independent variables on the right-hand side (RHS) are interval, ratio, and/or binary (dummy).

**Table 1.1 Ordinary Least Squares and Categorical Dependent Variable Models**

	Model	Dependent (LHS)	Estimation	Independent (RHS)
<b>OLS</b>	Ordinary least squares	Interval or ratio	Moment based method	A linear function of interval/ratio or binary variables $\beta_0 + \beta_1 X_1 + \beta_2 X_2 \dots$
<b>Categorical DV Models</b>	Binary response	Binary (0 or 1)	Maximum likelihood method	
	Ordinal response	Ordinal (1 <sup>st</sup> , 2 <sup>nd</sup> , 3 <sup>rd</sup> , ...)		
	Nominal response	Nominal (A, B, C ...)		
	Event count data	Count (0, 1, 2, 3...)		

Categorical dependent variable models adopt the maximum likelihood (ML) estimation method, whereas OLS uses the moment based method. The ML method requires an assumption about probability distribution functions, such as the logistic function and the complementary log-log

function. Logit models use the standard logistic probability distribution, while probit models assume the standard normal distribution. This document focuses on logit and probit models only, excluding regression models for event count data (e.g., negative binomial regression model and zero-inflated or zero-truncated regression models). Table 1.1 summarizes categorical dependent variable models in comparison with OLS.

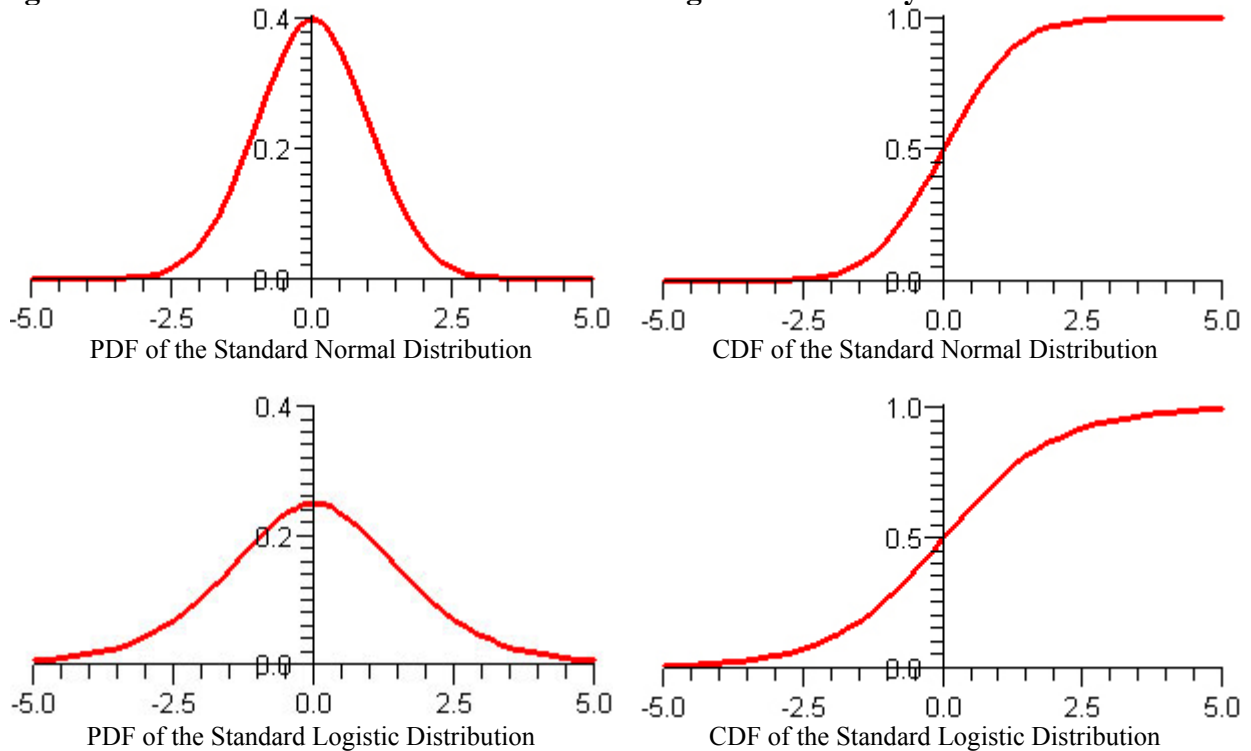
## 1.2 Logit Models versus Probit Models

How do logit models differ from probit models? The core difference lies in the distribution of errors (disturbances). In the logit model, errors are assumed to follow the standard logistic

distribution with mean 0 and variance  $\frac{\pi^2}{3}$ ,  $\lambda(\varepsilon) = \frac{e^\varepsilon}{(1+e^\varepsilon)^2}$ . The errors of the probit model are

assumed to follow the standard normal distribution,  $\phi(\varepsilon) = \frac{1}{\sqrt{2\pi}} e^{-\frac{\varepsilon^2}{2}}$  with variance 1.

**Figure 1.1 The Standard Normal and Standard Logistic Probability Distributions**



The probability density function (PDF) of the standard normal probability distribution has a higher peak and thinner tails than the standard logistic probability distribution (Figure 1.1). The standard logistic distribution looks as if someone has weighed down the peak of the standard normal distribution and strained its tails. As a result, the cumulative density function (CDF) of the standard normal distribution is steeper in the middle than the CDF of the standard logistic distribution and quickly approaches zero on the left and one on the right.

The two models, of course, produce different parameter estimates. In binary response models, the estimates of a logit model are roughly  $\pi/\sqrt{3}$  times larger than those of the probit model. These estimators, however, end up with almost the same standardized impacts of independent variables (Long 1997).

The choice between logit and probit models is more closely related to estimation and familiarity rather than theoretical and interpretive aspects. In general, logit models reach convergence fairly well. Although some (multinomial) probit models may take a long time to reach convergence, a probit model works well for bivariate models. As computing power improves and new algorithms are developed, importance of this issue is diminishing. For discussion on choosing logit and probit models, see Cameron and Trivedi (2009: 471-474).

### 1.3 Estimation in SAS, Stata, LIMDEP, R, and SPSS

SAS provides several procedures for categorical dependent variable models, such as PROC LOGISTIC, PROBIT, GENMOD, QLIM, MDC, PHREG, and CATMOD. Since these procedures support various models, a categorical dependent variable model can be estimated by multiple procedures. For example, you may run a binary logit model using PROC LOGISTIC, QLIM, GENMOD, and PROBIT. PROC LOGISTIC and PROC PROBIT of SAS/STAT have been commonly used, but PROC QLIM and PROC MDC of SAS/ETS have advantages over other procedures. PROC LOGISTIC reports factor changes in the odds and tests key hypotheses of a model.

**Table 1.2 Procedures and Commands for Categorical Dependent Variable Models**

	Model	SAS 9.2	Stata 11	LIMDEP 9	SPSS17
	<b>OLS</b> (Ordinary least squares)	REG	.regress	Regress\$	Regression
<b>Binary</b>	Binary logit	QLIM, LOGISTIC, GENMOD, PROBIT	.logit, .logistic	Logit\$	Logistic regression
	Binary probit	QLIM, LOGISTIC, GENMOD, PROBIT	.probit	Probit\$	Probit
<b>Bivariate</b>	Bivariate probit	QLIM	.biprobit	Bivariateprobit\$	-
	Ordinal logit	QLIM, LOGISTIC, GENMOD, PROBIT	.ologit	Ordered\$, Logit\$	Plum
<b>Ordinal</b>	Generalized logit	-	.gologit2*	-	-
	Ordinal probit	QLIM, LOGISTIC, GENMOD, PROBIT	.oprobit	Ordered\$	Plum
<b>Nominal</b>	Multinomial logit	LOGISTIC, CATMOD	.mlogit	Mlogit\$, Logit\$	Nomreg
	Conditional logit	LOGISTIC, MDC, PHREG	.clogit	Clogit\$, Logit\$	Coxreg
	Nested logit	MDC	.nlogit	Nlogit\$**	-
	Multinomial probit	-	.mprobit	-	-

\* A user-written command written by Williams (2005)

\*\* The Nlogit\$ command is supported by NLOGIT, a stand-alone package, which is sold separately.

The QLIM (Qualitative and Limited dependent variable Model) procedure analyzes various categorical and limited dependent variable regression models such as censored, truncated, and sample-selection models. PROC QLIM also handles Box-Cox regression and the bivariate probit model. The MDC (Multinomial Discrete Choice) procedure can estimate conditional logit and nested logit models.

Another advantage of using SAS is the Output Delivery System (ODS), which makes it easy to manage SAS output. ODS enables users to redirect the output to HTML (Hypertext Markup Language) and RTF (Rich Text Format) formats. Once SAS output is generated in a HTML document, users can easily handle tables and graphics especially when copying and pasting them into a wordprocessor document.

Unlike SAS, Stata has individualized commands for corresponding categorical dependent variable models. For example, the `.logit` and `.probit` commands respectively fit the binary logit and probit models, while `.mlogit` and `.nlogit` estimate the multinomial logit and nested logit models. Stata enables users to perform post-hoc analyses such as marginal effects and discrete changes in an easy manner.

The LIMDEP `Logit$` and `Probit$` commands support a variety of categorical dependent variable models that are addressed in Greene's *Econometric Analysis* (2003). The output format of LIMDEP 9 is slightly different from that of previous version, but key statistics remain unchanged. The nested logit model and multinomial probit model in LIMDEP are estimated by NLOGIT, a separate package. In R, `glm()` fits binary logit and probit models in the object-oriented programming concept. SPSS also supports some categorical dependent variable models and its output is often messy and hard to read. Stata and R are case-sensitive, but SAS, LIMDEP, and SPSS are not. Table 1.2 summarizes the procedures and commands used for categorical dependent variable models.

#### 1.4 Long and Freese's SPost

Stata users may benefit from user-written commands such as J. Scott Long and Jeremy Freese's SPost. This collection of user-written commands conducts many follow-up analyses of various categorical dependent variable models including event count data models. See section 2.2 for major SPost commands.

In order to install SPost, execute the following commands consecutively. Visit J. Scott Long's Web site at <http://www.indiana.edu/~jslsoc/> to get further information.

```
. net from http://www.indiana.edu/~jslsoc/stata/  
. net install spost9_ado, replace  
. net get spost9_do, replace
```

If a Stata command, function, or user-written command does not work in version 11, run the `.version` command to switch the interpreter to old one and execute that command again. For example, `normal()` was `norm()` in old versions.

```
. version 9
```

Also you may update Stata or reinstall user-written commands to get their latest version installed.

```
. update all
```

## 2. Binary Logit Regression Model

The binary logit model is represented as  $\text{Prob}(y = 1 | x) = \Lambda(x\beta) = \frac{\exp(x\beta)}{1 + \exp(x\beta)}$ , where  $\Lambda$  indicates a link function, the cumulative standard logistic distribution function. This chapter illustrates how to fit the binary logit model. The sample model considered here explores how social trust is affected by education, family income, age, gender, and WWW use.

### 2.1 Binary Logit Model in Stata (.logit)

Stata provides two equivalent commands for the binary logit model that present the same result in different ways. The `.logit` command produces coefficients with respect to logit (log of odds), while `.logistic` reports odd ratios.

```
. logistic trust educate income age male www
```

```
Logistic regression                Number of obs   =       1174
                                LR chi2(5)      =       128.68
                                Prob > chi2        =       0.0000
Log likelihood = -733.97164        Pseudo R2      =       0.0806
```

trust	Odds Ratio	Std. Err.	z	P> z	[95% Conf. Interval]
educate	1.163673	.0304619	5.79	0.000	1.105474 1.224935
income	1.030814	.0118919	2.63	0.009	1.007768 1.054387
age	1.028411	.0050091	5.75	0.000	1.01864 1.038276
male	1.292781	.162669	2.04	0.041	1.010228 1.654362
www	1.739745	.2885914	3.34	0.001	1.25686 2.408153

This model fits the data very well ( $p < .0000$ ) and all independent variables except for gender are statistically significant at the .01 level. Interpretation of the odds ratio will be discussed in Section 2.2. In order to get the coefficients (log of odds), simply run `.logit` without any argument right after the `.logistic` command.

```
. logit
(output is skipped)
```

Or you may run a separate `.logit` command with all arguments. Both commands report the same goodness-of-fit measures such as likelihood ratio and McFadden's pseudo  $R^2$ .

```
. logit trust educate income age male www
```

```
Iteration 0:  log likelihood = -798.31217
Iteration 1:  log likelihood = -734.25733
Iteration 2:  log likelihood = -733.97169
Iteration 3:  log likelihood = -733.97164
```

```
Logistic regression                Number of obs   =       1174
                                LR chi2(5)      =       128.68
                                Prob > chi2        =       0.0000
Log likelihood = -733.97164        Pseudo R2      =       0.0806
```

trust	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
-------	-------	-----------	---	------	----------------------

educate		.1515812	.0261774	5.79	0.000	.1002745	.2028879
income		.0303485	.0115364	2.63	0.009	.0077376	.0529595
age		.0280152	.0048707	5.75	0.000	.0184688	.0375616
male		.256796	.1258287	2.04	0.041	.0101762	.5034157
www		.5537383	.1658815	3.34	0.001	.2286165	.8788601
_cons		-4.983007	.478359	-10.42	0.000	-5.920574	-4.045441

A coefficient of `.logit` is the corresponding logarithmic transformed odds ratio of `.logistic`. For example, the coefficient of education is  $.1516 = \log(1.1637)$  or  $1.1637 = \exp(.1516)$ .

Stata has post-estimation commands that conduct follow-up analyses. The following `.predict` command with the `residual` option computes residuals and then stores them into a new variable `resid`.

```
. predict resid, residual
```

The `.test` and `.lrtest` commands respectively conduct the Wald test and likelihood ratio test. A large chi-squared rejects the null hypothesis that the parameter of education is zero. Education has a significant positive impact on social trust.

```
. test educate
```

```
( 1) [trust]educate = 0
      chi2( 1) =    33.53
      Prob > chi2 =    0.0000
```

Marginal effects and discrete changes are very useful when interpreting the result of a binary logit or probit model. The marginal effect of a continuous independent variable  $x_c$  is the partial derivative with respect to that variable. The discrete change of a binary independent variable (dummy variable)  $x_b$  is the difference in predicted probabilities of  $x_b = 1$  and  $x_b = 0$ , holding all other independent variables constant at their reference points.  $x_{-b}$  denotes all independent variables other than  $x_b$ . Marginal effects and discrete changes look similar but are not equal in conceptual and numerical senses.

$$\frac{\partial P(y=1|x)}{\partial x_c} = \frac{\exp(x\beta)}{[1 + \exp(x\beta)]^2} = \Lambda(x\beta)(1 - \Lambda(x\beta))\beta_c \quad (\text{marginal effect of } x_c)$$

$$\frac{\Delta P(y=1|x)}{\Delta x_b} = P(y=1|x_{-b}, x_b=1) - P(y=1|x_{-b}, x_b=0) \quad (\text{discrete change of } x_b)$$

The `.mfx` command with `dydx` (partial derivatives), the default option, computes marginal effects for continuous covariates and discrete changes for binary variables at the reference points after the estimation of a linear or nonlinear regression model. You may change reference points using the `at()` option; If this option is not specified, Stata by default uses means of independent variables as reference points. `mean` in the `at()` option below says that if a covariate is not listed in `at()`, its mean is used as its reference point.

```
. mfx, dydx at(mean educate=16 male=0 www=1)
```

Marginal effects after logit  
 $y = \text{Pr}(\text{trust})$  (predict)  
 $= .47534926$

variable	dy/dx	Std. Err.	z	P> z	[	95% C.I.	]	X
educate	.0378032	.0066	5.73	0.000	.024873	.050734		16
income	.0075687	.00287	2.63	0.008	.001934	.013203		24.6486
age	.0069868	.00121	5.75	0.000	.004606	.009367		41.3075
male*	.0640968	.03132	2.05	0.041	.002718	.125475		0
www*	.1329051	.03797	3.50	0.000	.058487	.207323		1

(\*) dy/dx is for discrete change of dummy variable from 0 to 1

The predicted probability of trusting most people is .4753 for female WWW users at the average age of 41 who graduated a college (16 years of education) and have average family income of 25 thousands dollars. Marginal effects and discrete changes are listed under  $dy/dx$ . For a year increase in education after college graduation, the predicted probability of trusting people will increase by 3.78 percent, holding other independent variables constant at the reference points (see the list of values under the label  $x$ ). WWW users are 13.29 percent more likely than non-users to trust people, holding other covariates at the reference points.

## 2.2 Using SPost Commands in Stata

SPost commands provide useful follow-up analysis commands (ado files) for categorical dependent variable models (Long and Freese 2003). The `.fitstat` command reports various goodness-of-fit measures such as log likelihood, McFadden's  $R^2$  (or Pseudo  $R^2$ ), Akaike Information Criterion (AIC), and Bayesian Information Criterion (BIC). 1467.943 labeled as  $D(1168)$  is  $-2 * \text{Log-likelihood}$  ( $= -2 * -733.972$ ) and  $1,168 = N - K = 1,174 - 6$ , where  $K$  denotes the number of parameters including the intercept.

```
. net install spost9_ado, replace from(http://www.indiana.edu/~jslsoc/stata/)
checking spost9_ado consistency and verifying not already installed...

. fitstat

Log-Lik Intercept Only:      -798.312   Log-Lik Full Model:      -733.972
D(1168):                    1467.943   LR(5):                  128.681
                             Prob > LR:          0.000
McFadden's R2:              0.081       McFadden's Adj R2:      0.073
ML (Cox-Snell) R2:         0.104       Cragg-Uhler(Nagelkerke) R2: 0.140
McKelvey & Zavoina's R2:   0.140       Efron's R2:             0.105
Variance of y*:            3.826       Variance of error:      3.290
Count R2:                  0.654       Adj Count R2:           0.175
AIC:                       1.261       AIC*n:                  1479.943
BIC:                       -6787.682    BIC':                   -93.340
BIC used by Stata:         1510.352    AIC used by Stata:      1479.943
```

The likelihood ratio statistic is based on the difference of log likelihoods between the null model and the full model.  $128.68 = -2 * [(-798.312) - (-733.972)]$ .

The binary logit (log of the odds) model can be expressed in a log-linear form of  $\ln \Omega(x) = x\beta$ , where  $\Omega(x)$  is the odds of the success ( $y=1$ ) given  $x$  (Long 1997: 79). The odds ratio is used to examine the change in the odds when an independent variable  $x_{odds}$  increases by  $\delta$ ; a odds ratio greater than 1 means that the odds increase as that variable increase by  $\delta$  (pp. 80-82).

$$\text{The odds: } \Omega(x) = \frac{P(y=1|x)}{P(y=0|x)} = \frac{P(y=1|x)}{1-P(y=1|x)} = \frac{\Lambda(x\beta)}{1-\Lambda(x\beta)}$$

$$\text{Odds ratio: } \frac{\Omega(x_{-odds}, x_{odds} + \delta)}{\Omega(x_{-odds}, x_{odds})} = \exp(\beta_{odds} \delta)$$

The `.listcoef` command produces a table of unstandardized coefficients (parameter estimates), factor (percent) changes in odds, and standardized coefficients. The `help` option helps read the output of `.listcoef`. Find factor changes in odds under the labels `e^b` and `e^bStdX`. Factor changes in odds are, in fact, the odds ratios that `.logistic` produced on page 6.

Long (1997) discusses interpretation of binary response models using factor changes in odds and predicted probabilities. For a unit increase in education, for example, the odds are expected to increase by a factor of  $1.1637 = \exp(.1516)$ . Alternatively, for a standard deviation change in education, the odds will change by a factor of  $1.4763 = \exp(.1516 * 2.5697)$ . Notice that the last column under `SDofX` lists standard deviations of covariates. The odds of trusting people are  $1.2928 = \exp(.2568)$  times larger for men than for women, holding all other variables constant.

`. listcoef, help`

logit (N=1174): Factor Change in Odds

Odds of: 1 vs 0

trust	b	z	P> z	e^b	e^bStdX	SDofX
educate	0.15158	5.791	0.000	1.1637	1.4763	2.5697
income	0.03035	2.631	0.009	1.0308	1.2068	6.1943
age	0.02802	5.752	0.000	1.0284	1.4559	13.4071
male	0.25680	2.041	0.041	1.2928	1.1364	0.4978
www	0.55374	3.338	0.001	1.7397	1.2554	0.4108

b = raw coefficient  
z = z-score for test of b=0  
P>|z| = p-value for z-test  
e^b = exp(b) = factor change in odds for unit increase in X  
e^bStdX = exp(b\*SD of X) = change in odds for SD increase in X  
SDofX = standard deviation of X

You may interpret factor change in odds in a reverse way. Pay attention to reverse of the `.listcoef` command. For a standard deviation change in education, the odds of having NO social trust are expected to decrease by a factor of  $.6774 = \exp(-.1516 * 2.5697)$ . The odds of NOT trusting people are  $.7735 = \exp(-.2568)$  times smaller for men than for women. The labels `e^b` and `e^bStdX` below should be  $e^{(-b)}$  and  $e^{(-bStdX)}$ , respectively.

`. listcoef, reverse`

logit (N=1174): Factor Change in Odds

Odds of: 0 vs 1

trust	b	z	P> z	e^b	e^bStdX	SDofX
educate	0.15158	5.791	0.000	0.8593	0.6774	2.5697
income	0.03035	2.631	0.009	0.9701	0.8286	6.1943
age	0.02802	5.752	0.000	0.9724	0.6869	13.4071

```

male | 0.25680 2.041 0.041 0.7735 0.8800 0.4978
www  | 0.55374 3.338 0.001 0.5748 0.7966 0.4108
-----

```

Alternatively, you may use percent changes in the odds by adding the `percent` option. For example, the odds of trusting people are 29.3 percent larger for men than for women, holding all other covariates constant.

```
. listcoef, percent help
```

```
logit (N=1174): Percentage Change in Odds
```

```
Odds of: 1 vs 0
```

```

-----
trust |      b      z  P>|z|    %    %StdX   SDofX
-----+-----
educate | 0.15158  5.791  0.000   16.4   47.6   2.5697
income  | 0.03035  2.631  0.009    3.1   20.7   6.1943
age     | 0.02802  5.752  0.000    2.8   45.6  13.4071
male    | 0.25680  2.041  0.041   29.3   13.6   0.4978
www     | 0.55374  3.338  0.001   74.0   25.5   0.4108
-----

```

```

b = raw coefficient
z = z-score for test of b=0
P>|z| = p-value for z-test
% = percent change in odds for unit increase in X
%StdX = percent change in odds for SD increase in X
SDofX = standard deviation of X

```

The `.prvalue` command lists predicted probabilities of positive and negative outcomes for a given set of values for the independent variables. The following example predicts, as shown in `.mfx` above, that 47.53 percent of female WWW users will trust most people at the reference points (`educate=16`, `income=24.65`, `age=41.31`), while 52.47 percent will not.

```
. prvalue, x(educate=16 male=0 www=1) rest(mean)
```

```
logit: Predictions for trust
```

```
Confidence intervals by delta method
```

```

                    95% Conf. Interval
Pr(y=1|x):          0.4753  [ 0.4277, 0.5230]
Pr(y=0|x):          0.5247  [ 0.4770, 0.5723]

educate  income      age      male      www
x=       16  24.648637  41.307496      0      1

```

The `.prtab` command constructs a table of predicted values (probabilities) for all combinations of categorical variables listed. Both `.prtab` and `.prvalue` report the same predicted probability of .4753 that female WWW users trust most people. The table below suggests that male WWW users are more likely to trust than their counterparts (53.94 percent versus 34.24 percent, respectively). The `x()` option specifies particular values of covariates other than their means as reference points. The `rest()` option sets the reference points of independent variables that are not specified in `x()`.

```
. prtab male www, x(educate=16 male=0 www=1) rest(mean)
```

```
logit: Predicted probabilities of positive outcome for trust
```

```
-----
```

Gender	WWW Use	
	Non-users	Users
Female	0.3424	0.4753
Male	0.4024	0.5394

```
x=      educate      income      age      male      www
      16  24.648637  41.307496      0      1
```

The most useful command for binary response models is `.prchange`, which calculates marginal effects and discrete changes at a given set of values of independent variables. The predicted probability of .4753 and the marginal effects (discrete changes) are the same as what `.mfx` produced above. Read marginal effects under the last `MargEfct` (or `-+1/2`) column and discrete changes under `0->1` (when changing the value from 0 to 1). For an additional year of education after college, the predicted probability of trusting people is expected to increase by 3.78 percent (marginal effect) when holding all other covariates constant at their reference points. WWW users are 13.29 percent (discrete change) more likely than non-users to trust people, holding other variable at their reference points.

```
. prchange, x(educate=16 male=0 www=1) rest(mean)
```

```
logit: Changes in Probabilities for trust
```

	min->max	0->1	-+1/2	-+sd/2	MargEfct
educate	0.5264	0.0111	0.0378	0.0968	0.0378
income	0.1936	0.0064	0.0076	0.0468	0.0076
age	0.4397	0.0049	0.0070	0.0934	0.0070
male	0.0641	0.0641	0.0640	0.0319	0.0640
www	0.1329	0.1329	0.1372	0.0567	0.1381

```
Pr(y|x)      0      1
            0.5247 0.4753
```

```
      educate      income      age      male      www
x=      16  24.6486  41.3075      0      1
sd_x=  2.56971  6.19427  13.4071  .497765  .410755
```

SPost `.prgen` computes a series of predictions (predicted probabilities in this case) by holding all variables but one interval variable constant and allowing that variable to vary (Long and Freese 2003). The first command below computes predicted probabilities that male WWW users (`male=1` and `www=1`) trust most people when education changes from 0 through 20 years, holding other independent variables at the reference points, and then stores them into new variables, whose names begin with `Logit_ed11`.

```
. prgen educate, from(0) to(20) ncases(20) x(male=1 www=1) rest(mean) gen(Logit_ed11)
```

```
logit: Predicted values as educate varies from 0 to 20.
```

```
      educate      income      age      male      www
x=  14.24276  24.648637  41.307496      1      1
```

```
. prgen educate, from(0) to(20) ncases(20) x(male=1 www=0) rest(mean) gen(Logit_ed10)
```

```
logistic: Predicted values as educate varies from 0 to 20.
```

```
      educate      income      age      male      www
x=  14.24276  24.648637  41.307496      1      0
```

```
. prgen educate, from(0) to(20) ncases(20) x(male=0 www=1) rest(mean) gen(Logit_ed01)
```

logistic: Predicted values as educate varies from 0 to 20.

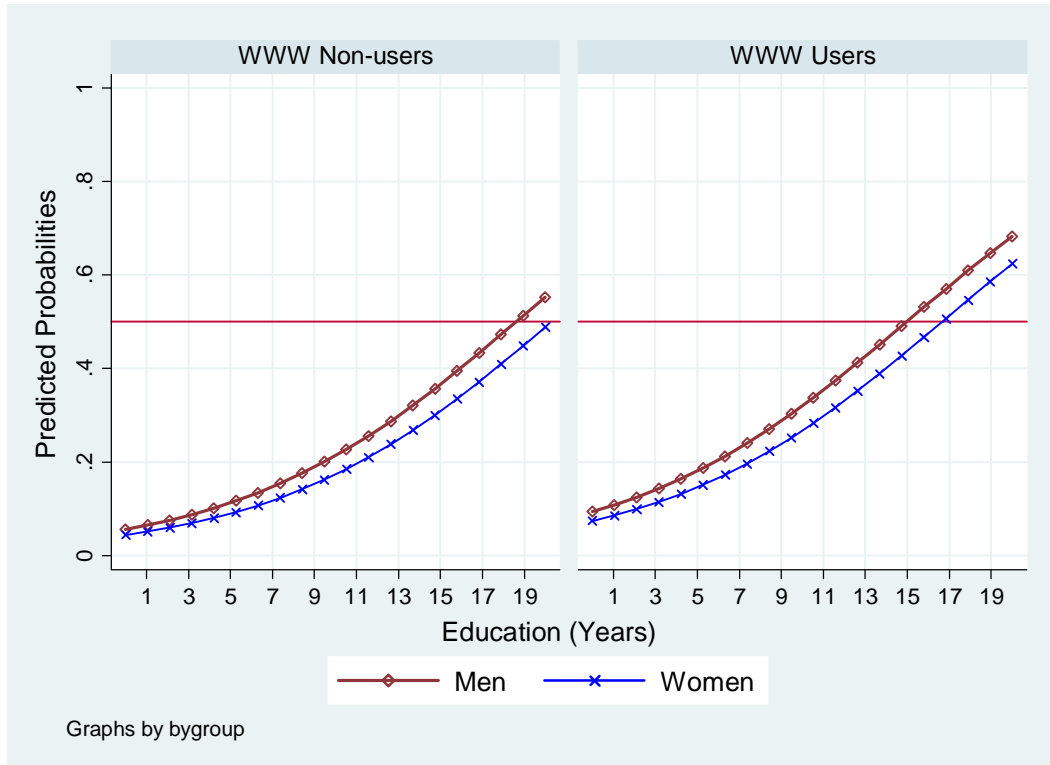
	educate	income	age	male	www
x=	14.24276	24.648637	41.307496	0	1

```
. prgen educate, from(0) to(20) ncases(20) x(male=0 www=0) rest(mean) gen(Logit_ed00)
```

logistic: Predicted values as educate varies from 0 to 20.

	educate	income	age	male	www
x=	14.24276	24.648637	41.307496	0	0

Figure 2.1 Predicted Probabilities of Trusting Most People (Binary Logit Model)



After generating predicted probabilities of other groups (male WWW non-users, female users, and female non-users), you can draw Figure 2.1. See the Stata script in Appendix for necessary data manipulation. Figure 2.1 suggests that education and WWW use influence social trust significantly but gender does not.

### 2.3 Binary Logit Model in SAS: PROC LOGISTIC and PROC PROBIT

SAS has several procedures for the binary logit model such as LOGISTIC, PROBIT, GENMOD, and QLIM procedures. PROC LOGISTIC is commonly used for the binary logit model, but PROC PROBIT is also able to estimate the binary logit model.

Unlike PROC QLIM, LOGISTIC, PROBIT, and GENMOD procedures by default use a smaller value in the dependent variable as success (positive event). As a consequence, magnitudes of the coefficients remain the same, but their signs are opposite to those of PROC QLIM, Stata, and LIMDEP. The DESCENDING (DESC) option in PROC LOGISTIC and

PROC GENMOD forces SAS to use a larger value as success. Notice that a SAS procedure is comprised of a series of statements, each of which ends with a semi-colon.

```
PROC LOGISTIC DESCENDING DATA = masil.gss_cdvm;
  MODEL trust = educate income age male www;
RUN;
```

Alternatively, you may explicitly specify the category of successful event using the EVENT option. EVENT=LAST (or EVENT='1') use the last ordered category (1) as a successful event. Both approaches end up with the same result.

```
PROC LOGISTIC DATA = masil.gss_cdvm;
  MODEL trust(EVENT=LAST) = educate income age male www;
RUN;
```

#### The LOGISTIC Procedure

##### Model Information

Data Set	MASIL.GSS_CDVM	
Response Variable	trust	trust
Number of Response Levels	2	
Model	binary logit	
Optimization Technique	Fisher's scoring	

Number of Observations Read	1174
Number of Observations Used	1174

##### Response Profile

Ordered Value	trust	Total Frequency
1	1	492
2	0	682

Probability modeled is trust=1.

##### Model Convergence Status

Convergence criterion (GCONV=1E-8) satisfied.

##### Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	1598.624	1479.943
SC	1603.693	1510.352
-2 Log L	1596.624	1467.943

## Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	128.6811	5	<.0001
Score	121.5344	5	<.0001
Wald	109.6453	5	<.0001

## Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept	1	-4.9830	0.4784	108.5101	<.0001
educate	1	0.1516	0.0262	33.5302	<.0001
income	1	0.0303	0.0115	6.9200	0.0085
age	1	0.0280	0.00487	33.0824	<.0001
male	1	0.2568	0.1258	4.1650	0.0413
www	1	0.5537	0.1659	11.1431	0.0008

## Odds Ratio Estimates

Effect	Point Estimate	95% Wald Confidence Limits	
educate	1.164	1.105	1.225
income	1.031	1.008	1.054
age	1.028	1.019	1.038
male	1.293	1.010	1.654
www	1.740	1.257	2.408

## Association of Predicted Probabilities and Observed Responses

Percent Concordant	68.4	Somers' D	0.371
Percent Discordant	31.3	Gamma	0.373
Percent Tied	0.4	Tau-a	0.181
Pairs	335544	c	0.686

Stata and SAS produce the same result. Log likelihood is  $-733.9716 = (1467.943/-2)$ ; SAS report  $-2 * \log \text{likelihood}$  1467.943. Likelihood ratio is  $128.681 = 1596.624 - 1467.943$ . McFadden's pseudo  $R^2$  is  $.0806 = 1 - (1467.943/1596.624)$ . AIC and BIC (or Schwarz information criterion) are 1479.943 and 1510.352, respectively, in both outputs. Parameter estimates and their standard errors are same. However, Stata and SAS respectively conduct z test and Wald test to examine the effects of individual independent variables but end up with same p-values except for rounding errors. For example, Stata's z score 5.79 for education is the square root of the Wald statistic 33.53.

If you want to get the output in the HTML format, use ODS statements before and after a SAS procedure. ODS HTML redirects SAS output to the HTML format. The output is skipped.

```
ODS HTML;
PROC LOGISTIC . . .
. . .
ODS HTML CLOSE;
```

PROC LOGISTIC by default reports odds changes when independent variables increase by a unit. The odds changes (ratios) under Odds Ratio Estimates are the same as what Stata `.listcoef` produced in Section 2.2. For a unit (\$1,000) increase in family income, the odds of having social trust are expected to change by a factor of  $1.031 = \exp(.0303)$ , holding all other covariates constant. The odds of having social trust are  $1.293 = \exp(.2568)$  times larger for men than for women; conversely, the odds of having no social trust are  $.7734 = \exp(-.2568)$  times smaller for men than for women.

The UNITS statement specifies a unit other than means of covariates. The SD in UNITS indicates a standard deviation increase in covariates listed (`educate`, `income`, and `age` in this example). UNITS adds factor changes in odds to the end of the LOGISTIC output. Read numbers under Odds Ratios (other output is skipped below). For a standard deviation increase in family income, the odds are expected to increase by a factor of  $1.207 = \exp(.0303 * 6.1943)$ . You may find the same number under `e^bStdX` of `.listcoef` in Section 2.2.

```
PROC LOGISTIC DATA = masil.gss_cdvm;
  MODEL trust(EVENT='1') = educate income age male www;
  UNITS educate=SD income=SD age=SD;
RUN;
```

	Odds Ratios		
Effect	Unit	Estimate	
educate	2.5697	1.476	
income	6.1943	1.207	
age	13.4071	1.456	

Let us compute marginal effects manually. See Park (2004) for computation in detail. If you are not familiar with SAS, you may skip this part. The first step is to get parameter estimates and reference points. In PROC LOGISTIC, add `OUTEST=masil.blm` to store parameter estimates into a SAS data set `masil.blm`. PROC MEANS with MEAN and STD computes means and standard deviations of variables listed in the VAR statement and then store them into `masil.meanX`. Notice that SAS, unlike Stata and R, is not case-insensitive.

```
PROC LOGISTIC DESCENDING DATA = masil.gss_cdvm OUTEST=masil.blm;
  MODEL trust = educate income age male www;

PROC MEANS MEAN STD DATA = masil.gss_cdvm;
  VAR educate income age male www;
  OUTPUT OUT=masil.meanX;
RUN;
(output is skipped)
```

Next, convert two SAS data sets into matrices, `bHat` and `X` in PROC IML. Then, compute predicted probability and marginal effects. Pay attention to comments enclosed by `/*` and `*/`.

```

PROC IML;
USE masil.blm; /* get a row vector of parameter estimates */
READ ALL VAR{Intercept educate income age male www} INTO bHat;
K=NCOL(bHat); /* get the number of regressors */

USE masil.meanX;
READ ALL VAR{educate income age male www} INTO X;
meanX = {1} || X[4,]; /* a row vector of means of independent variables */
sdX = {0} || X[5,]; /* a row vector of standard deviations of independent variables */

referX = meanX; /* set reference points */
referX[1,2]=16; referX[1,5]=0; referX[1,6]=1; /* education=16, male=0, www=1 */

xb = bHat * T(referX);
prob = exp(xb)/(1+exp(xb)); /* compute a predicted probability */

PRINT referX prob;

margin = prob * (1-prob) * T(bHat); /* compute marginal effects */
marginSD = prob * (1-prob) * T(bHat # sdX);

result = T(bHat) || T(exp(bHat))||T(exp(bHat # sdX)) || margin||marginSD || T(meanX)||T(sdX);
result = result[2:K,];

PRINT result[ROWNAME={"educate", "income", "age", "male", "www"}
             COLNAME={"b" "exp(b)" "exp(b*sdX)" "MargEffect" "MargEffect(SD)" "Mean of X" "SD of X"}];

QUIT; /* terminate PROC IML */

```

The following is the output of the PROC IML above. Compare marginal effects with what `.prchange` reported in Section 2.2. Notice that `.0640` and `.1381` are not correct discrete changes of gender and WWW use, respectively. Factor changes in the odds are also listed under labels `exp(b)` and `exp(b*sdX)`.

	referX				prob			
	1	16	24.648637	41.307496	0	1	0.4753497	
	result							
	b	exp(b)	exp(b*sdX)	MargEffect	MargEffect(SD)	Mean of X	SD of X	
educate	0.1515807	1.1636722	1.4762701	0.0378031	0.097143	14.24276	2.5697123	
income	0.0303475	1.0308127	1.2068103	0.0075684	0.046881	24.648637	6.1942699	
age	0.0280151	1.0284112	1.4558671	0.0069867	0.0936722	41.307496	13.407127	
male	0.2567949	1.29278	1.1363525	0.0640427	0.0318782	0.4505963	0.4977653	
www	0.5537335	1.7397362	1.255393	0.1380969	0.056724	0.7853492	0.4107548	

PROC PROBIT is primarily designed for the binary probit model but can estimate the same binary logit model as well. The `/DIST=LOGISTIC` option indicates the link function (probability distribution) to be used in maximum likelihood estimation.

```

PROC PROBIT DATA = masil.gss_cdvm;
MODEL trust = educate income age male www /DIST=LOGISTIC;

```

**RUN;**

The Probit Procedure

Model Information

Data Set	MASIL.GSS_CDVM	
Dependent Variable	trust	trust
Number of Observations	1174	
Name of Distribution	Logistic	
Log Likelihood	-733.97164	

Number of Observations Read	1174
Number of Observations Used	1174

Class Level Information

Name	Levels	Values
trust	2	0 1

Response Profile

Ordered Value	trust	Total Frequency
1	0	682
2	1	492

PROC PROBIT is modeling the probabilities of levels of trust having LOWER Ordered Values in the response profile table.

Algorithm converged.

Type III Analysis of Effects

Effect	DF	Wald	
		Chi-Square	Pr > ChiSq
educate	1	33.5304	<.0001
income	1	6.9204	0.0085
age	1	33.0827	<.0001
male	1	4.1650	0.0413
www	1	11.1433	0.0008

Analysis of Maximum Likelihood Parameter Estimates

Parameter	DF	Estimate	Standard Error	95% Confidence Limits		Chi-Square	Pr > ChiSq
Intercept	1	4.9830	0.4784	4.0454	5.9206	108.51	<.0001
educate	1	-0.1516	0.0262	-0.2029	-0.1003	33.53	<.0001

income	1	-0.0303	0.0115	-0.0530	-0.0077	6.92	0.0085
age	1	-0.0280	0.0049	-0.0376	-0.0185	33.08	<.0001
male	1	-0.2568	0.1258	-0.5034	-0.0102	4.17	0.0413
www	1	-0.5537	0.1659	-0.8789	-0.2286	11.14	0.0008

Unlike PROC LOGISTIC, PROC PROBIT does not have the DESCENDING (or DESC) option. Therefore, you have to switch the signs of coefficients when comparing with PROC LOGISTIC, Stata, and LIMDEP. PROC PROBIT does not have the UNITS statement to compute factor changes in the odds.

## 2.4 Binary Logit Model in SAS: PROC QLIM and PROC GENMOD

PROC QLIM estimates not only logit and probit models, but also censored, truncated, and sample-selected models. You may provide the probability distribution of a dependent variable in the ENDOGENOUS statement or in the DISCRETE option of the MODEL statement.

```
PROC QLIM DATA=masil.gss_cdv;
  MODEL trust = educate income age male www;
  ENDOGENOUS trust ~ DISCRETE(DIST=LOGIT);

PROC QLIM DATA=masil.gss_cdv;
  MODEL trust = educate income age male www /DISCRETE(DIST=LOGIT);
RUN;
```

### The QLIM Procedure

#### Discrete Response Profile of trust

Index	Value	Frequency	Percent
1	0	682	58.09
2	1	492	41.91

### Model Fit Summary

Number of Endogenous Variables	1
Endogenous Variable	trust
Number of Observations	1174
Log Likelihood	-733.97164
Maximum Absolute Gradient	0.0000275
Number of Iterations	13
Optimization Method	Quasi-Newton
AIC	1480
Schwarz Criterion	1510

### Goodness-of-Fit Measures

Measure	Value	Formula
Likelihood Ratio (R)	128.68	$2 * (\text{LogL} - \text{LogL0})$
Upper Bound of R (U)	1596.6	$- 2 * \text{LogL0}$
Aldrich-Nelson	0.0988	$R / (R+N)$
Cragg-Uhler 1	0.1038	$1 - \exp(-R/N)$

Cragg-Uhler 2	0.1397	$(1 - \exp(-R/N)) / (1 - \exp(-U/N))$
Estrella	0.108	$1 - (1 - R/U)^{(U/N)}$
Adjusted Estrella	0.0981	$1 - ((\text{Log}L - K) / \text{Log}L0)^{(-2/N * \text{Log}L0)}$
McFadden's LRI	0.0806	$R / U$
Veall-Zimmermann	0.1714	$(R * (U+N)) / (U * (R+N))$
McKelvey-Zavoina	0.3489	

N = # of observations, K = # of regressors

Algorithm converged.

#### Parameter Estimates

Parameter	DF	Estimate	Standard Error	t Value	Approx Pr >  t
Intercept	1	-4.983009	0.478382	-10.42	<.0001
educate	1	0.151581	0.026178	5.79	<.0001
income	1	0.030349	0.011536	2.63	0.0085
age	1	0.028015	0.004871	5.75	<.0001
male	1	0.256796	0.125829	2.04	0.0413
www	1	0.553738	0.165881	3.34	0.0008

PROC QLIM produces various goodness-of-fit measures and, unlike other procedures, reports  $t$  scores, which are the same as  $z$  score in Stata (see Section 2.1). Therefore, PROC QLIM is more comparable to Stata and LIMDEP than other alternative procedures in SAS.

PROC GENMOD provides flexible methods to estimate generalized linear and nonlinear models. The DISTRIBUTION (DIST) and the LINK=LOGIT options respectively specify a probability distribution and a link function.

```
PROC GENMOD DATA = masil.gss_cdvm DESC;
  MODEL trust = educate income age male www /DIST=BINOMIAL LINK=LOGIT;
RUN;
```

#### The GENMOD Procedure

##### Model Information

Data Set	MASIL.GSS_CDVM
Distribution	Binomial
Link Function	Logit
Dependent Variable	trust trust

Number of Observations Read	1174
Number of Observations Used	1174
Number of Events	492
Number of Trials	1174

##### Response Profile

Ordered Value	trust	Total Frequency
1	1	492
2	0	682

PROC GENMOD is modeling the probability that trust='1'.

Criteria For Assessing Goodness Of Fit

Criterion	DF	Value	Value/DF
Log Likelihood		-733.9716	
Full Log Likelihood		-733.9716	
AIC (smaller is better)		1479.9433	
AICC (smaller is better)		1480.0153	
BIC (smaller is better)		1510.3523	

Algorithm converged.

Analysis Of Maximum Likelihood Parameter Estimates

Parameter	DF	Estimate	Standard Error	Wald	95% Confidence Limits	Wald Chi-Square	Pr > ChiSq
Intercept	1	-4.9830	0.4784	-5.9206	-4.0454	108.51	<.0001
educate	1	0.1516	0.0262	0.1003	0.2029	33.53	<.0001
income	1	0.0303	0.0115	0.0077	0.0530	6.92	0.0085
age	1	0.0280	0.0049	0.0185	0.0376	33.08	<.0001
male	1	0.2568	0.1258	0.0102	0.5034	4.17	0.0413
www	1	0.5537	0.1659	0.2286	0.8789	11.14	0.0008
Scale	0	1.0000	0.0000	1.0000	1.0000		

NOTE: The scale parameter was held fixed.

Instead of the LINK=LOGIT option, you may provide a corresponding link function manually using the FWDLINK and INVLINK statements. The following is an example.

```
PROC GENMOD DATA = masil.gss_cdvms DESC;
  FWDLINK link=LOG(_MEAN_/ (1- _MEAN_));
  INVLINK invlink=1/(1+EXP(-1*_XBETA_));
  MODEL trust = educate income age male www /DIST=BINOMIAL;
RUN;
(output is skipped)
```

## 2.5 Binary Logit Model in R

In R, `glm()` fits binary logit and probit models. This function returns associated statistics and functions such as `coef()` and `vcov()` in an object. Unlike Stata and SAS, R does not give you all answers with a single function. Accordingly, you need to get specific answers using statistics and functions that `glm()` returns.

Let us read a data set first using `read.table()`. The following example reads a CSV file and saves into a data frame `df`. A delimiter is specified in `sep=' '` and `header=T` reads variable names from the first row. The `attach()` function adds the data frame to R search path so that variables in the data frame are accessed by their names alone (without their data frame name).

```
> df<-read.table('http://www.indiana.edu/~statmath/stat/all/cdvm/gss_cdvm.csv',
+               sep=',', header=T)
> attach(df)
```

In the `glm()` below, a dependent variable is followed by a tilde (~) and a list of independent variables separated by a plus (+) sign. The `family=` option specifies a link function. The `glm()` returns associated statistics and functions in an object `blm`. `summary(blm)` reports the summary of the estimated binary logit model.

```
> blm<-glm(trust~educate+income+age+male+www, data=df, family=binomial(link="logit"))
> summary(blm)

Call:
glm(formula = trust ~ educate + income + age + male + www, family = binomial(link = "logit"),
    data = df)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.8263  -0.9987  -0.6752   1.1494   2.1516

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept) -4.983009   0.478359 -10.417  < 2e-16 ***
educate      0.151581   0.026177   5.791 7.02e-09 ***
income      0.030349   0.011536   2.631 0.008522 **
age         0.028015   0.004871   5.752 8.83e-09 ***
male        0.256796   0.125829   2.041 0.041267 *
www         0.553738   0.165881   3.338 0.000843 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 1596.6  on 1173  degrees of freedom
Residual deviance: 1467.9  on 1168  degrees of freedom
AIC: 1479.9

Number of Fisher Scoring iterations: 4
```

R reports the same parameter estimates, standard errors, and z scores that Stata produced. R does not, however, display goodness-of-fit measures except for AIC and, like SAS PROC LOGISTIC, returns  $-2 \times \log$  likelihood of null and full models (see Section 2.3) instead. For instance, 1,467.9 of Residual deviance: is  $-2 \times \log$  likelihood of the full model. `df.null` (=1,173) and `df.residual` (=1,168) are degrees of freedom of null and full models, respectively. Therefore, the likelihood ratio and its p-value are computed as,

```
> blm$deviance/-2
[1] -733.9716

> AIC(blm)
[1] 1479.943

> LRtest<-blm$null.deviance - blm$deviance
> LRtest
[1] 128.6811
```

```
> dchisq(LRtest, blm$df.null - blm$df.residual)
[1] 2.214737e-26
```

The likelihood ratio is 128.6811, which is large enough to reject the null hypothesis of poor fit (no difference between null and full models). McFadden's pseudo  $R^2$  is computed on the basis of the two deviances (log likelihoods of null and full models):  $.0806=1-(1467.9/1596.6)$ . Notice that a comment begins with #.

```
> 1-bpm$deviance/bpm$null.deviance # McFadden's pseudo R square
[1] 0.08056336
```

Now, let us compute factor changes in the odds of having success. Create vectors of means and standard deviations of covariates using `c()`, `mean()`, and `sd()`. Notice that 1 is for the intercept. `bHat` and `K` are a vector of parameter estimates and a scalar for the length of `bHat` (number of parameters).

```
> meanX<-c(1, mean(educate), mean(income), mean(age), mean(male), mean(www))
> sdX<-c(1, sd(educate), sd(income), sd(age), sd(male), sd(www))
> bHat<-coef(blm) # vector of parameter estimates
> K<-length(bHat) # the number of parameters
```

Next, compute factor changes of the odds. The following `cbind()` combines individual vectors into a matrix. `exp(bHat*sdX)` is factor changes when covariates increase by their standard deviations. `colnames(fcOdds)` puts column names to the data frame `fcOdds`.

```
> fcOdds<-cbind(bHat, exp(bHat), exp(bHat*sdX), meanX, sdX)
> fcOdds<-fcOdds[2:K,]
> colnames(fcOdds)<-c("b", "e^b", "e^(b*sd)", "Mean of X", "SD of X")
```

The following output is very similar to what `.listcoef` produced in Section 2.2.

```
> fcOdds

      b      exp(b) exp(b*sd) Mean of X      SD of X
educate 0.15158121 1.163673  1.476272 14.2427598  2.5697123
income  0.03034856 1.030814  1.206818 24.6486371  6.1942699
age      0.02801520 1.028411  1.455869 41.3074957 13.4071272
male     0.25679598 1.292781  1.136353  0.4505963  0.4977653
www      0.55373840 1.739745  1.255396  0.7853492  0.4107548
```

Finally, compute marginal effects at the same reference points. `%%` below obtains the element by element product, a scalar of  $xb$  in this case. The scalar `prob` contains the predicted probability of 47.53 percent that female WWW users with 16 years of education (`educate=16`, `male=0`, and `www=1`) trust most people, holding other covariates at their means.

```
> referX<-c(1, 16, mean(income), mean(age), 0, 1) # set reference points
> xb<-bHat %% referX # element by element product

> prob<-exp(xb)/(1+exp(xb)) # compute a predicted probability
> prob
      [,1]
[1,] 0.4753492
```

Marginal effects are  $\Lambda(x\beta)(1 - \Lambda(x\beta))\beta_c$  in the binary logit model. When covariates increase by their standard deviations from the reference points, the marginal effects are `prob*(1-prob)*bHat*sdX`. Compare the following result with what `.prchange` computed in Section 2.2

and the PROC IML output in Section 2.3. Notice that .0640 and .1381 below are not discrete changes of gender and WWW use. See Section 3.4 for computing discrete changes.

```
> margEffect<-cbind(bHat, prob*(1-prob)*bHat, prob*(1-prob)*bHat*sdX, meanX,sdX)
> margEffect<-margEffect[2:K,]
> colnames(margEffect)<-c("b", "MargEffect", "MargEffect(SD)", "Mean of X", "SD of X")
> margEffect
```

	b	MargEffect	MargEffect(SD)	Mean of X	SD of X
educate	0.15158121	0.037803193	0.09714333	14.2427598	2.5697123
income	0.03034856	0.007568699	0.04688256	24.6486371	6.1942699
age	0.02801520	0.006986775	0.09367259	41.3074957	13.4071272
male	0.25679598	0.064042951	0.03187836	0.4505963	0.4977653
www	0.55373840	0.138098116	0.05672447	0.7853492	0.4107548

## 2.6 Binary Logit Model in LIMDEP (Logit\$)

LIMDEP can read data in the ASCII text (CSV) and Excel format. The following script clears the worksheet (RESET\$), defines data size (ROWS;999999\$), and then reads an Excel file gss\_cdvm.xls. Notice that each command ends with \$ and subcommands are separated by a semi-colon.

```
RESET$
ROWS;999999$
READ;FILE="C:\Temp\Limdep\gss_cdvm.xls"$
```

The Logit\$ command estimates various logit models in LIMDEP. A dependent variable is specified in the Lhs= (left-hand side) subcommand and a list of independent variables in the Rhs= (right-hand side). You have to explicitly specify ONE for the intercept.

```
LOGIT;Lhs=TRUST;
      Rhs=ONE, EDUCATE, INCOME, AGE, MALE, WWW$
```

Normal exit from iterations. Exit status=0.

```
+-----+
| Binary Logit Model for Binary Choice
| Maximum Likelihood Estimates
| Model estimated: Sep 09, 2009 at 04:25:56PM.
| Dependent variable          TRUST
| Weighting variable         None
| Number of observations      1174
| Iterations completed        5
| Log likelihood function     -733.9716
| Number of parameters        6
| Info. Criterion: AIC =      1.26060
|   Finite Sample: AIC =      1.26066
| Info. Criterion: BIC =      1.28650
| Info. Criterion: HQIC =     1.27037
| Restricted log likelihood   -798.3122
| McFadden Pseudo R-squared  .0805957
| Chi squared                 128.6811
| Degrees of freedom          5
| Prob[ChiSqd > value] =      .0000000
| Hosmer-Lemeshow chi-squared = 3.64573
| P-value= .88759 with deg.fr. = 8
+-----+
+-----+-----+-----+-----+-----+
|Variable| Coefficient | Standard Error |b/St.Er.|P[|Z|>z]| Mean of X|
+-----+-----+-----+-----+-----+
+-----+Characteristics in numerator of Prob[Y = 1]
Constant|  -4.98300913  .47835906  -10.417  .0000
EDUCATE |   .15158121   .02617738   5.791   .0000  14.2427598
```

INCOME	.03034856	.01153642	2.631	.0085	24.6486371
AGE	.02801520	.00487072	5.752	.0000	41.3074957
MALE	.25679598	.12582872	2.041	.0413	.45059625
WWW	.55373840	.16588151	3.338	.0008	.78534923

```

+-----+
| Information Statistics for Discrete Choice Model.
|
| M=Model MC=Constants Only M0=No Model
| Criterion F (log L) -733.97164 -798.31217 -813.75479
| LR Statistic vs. MC 128.68107 .00000 .00000
| Degrees of Freedom 5.00000 .00000 .00000
| Prob. Value for LR .00000 .00000 .00000
| Entropy for probs. 733.97164 798.31217 813.75479
| Normalized Entropy .90196 .98102 1.00000
| Entropy Ratio Stat. 159.56630 30.88523 .00000
| Bayes Info Criterion 1.28048 1.39009 1.41640
| BIC(no model) - BIC .13592 .02631 .00000
| Pseudo R-squared .08060 .00000 .00000
| Pct. Correct Pred. 65.41738 .00000 50.00000
| Means: y=0 y=1 y=2 y=3 y=4 y=5 y=6 y>=7
| Outcome .5809 .4191 .0000 .0000 .0000 .0000 .0000 .0000
| Pred.Pr .5809 .4191 .0000 .0000 .0000 .0000 .0000 .0000
| Notes: Entropy computed as Sum(i)Sum(j)Pfit(i,j)*logPfit(i,j).
| Normalized entropy is computed against M0.
| Entropy ratio statistic is computed against M0.
| BIC = 2*criterion - log(N)*degrees of freedom.
| If the model has only constants or if it has no constants,
| the statistics reported here are not useable.
+-----+

```

```

+-----+
| Fit Measures for Binomial Choice Model
| Logit model for variable TRUST
+-----+
| Proportions P0= .580920 P1= .419080
| N = 1174 N0= 682 N1= 492
| LogL= -733.972 LogL0= -798.312
| Estrella = 1-(L/L0)^(-2L0/n) = .10799
+-----+
| Efron | McFadden | Ben./Lerman
| .10474 | .08060 | .56407
| Cramer | Veall/Zim. | Rsqrd_ML
| .10469 | .17142 | .10382
+-----+
| Information Akaike I.C. Schwarz I.C.
| Criteria 1.26060 1.28650
+-----+

```

```

+-----+
| Predictions for Binary Choice Model. Predicted value is
| 1 when probability is greater than .500000, 0 otherwise.
| Note, column or row total percentages may not sum to
| 100% because of rounding. Percentages are of full sample.
+-----+
| Actual | Predicted Value | Total Actual |
| Value | 0 1 |
+-----+
| 0 | 538 ( 45.8%) | 144 ( 12.3%) | 682 ( 58.1%) |
| 1 | 262 ( 22.3%) | 230 ( 19.6%) | 492 ( 41.9%) |
+-----+
| Total | 800 ( 68.1%) | 374 ( 31.9%) | 1174 (100.0%) |
+-----+

```

```

=====
Analysis of Binary Choice Model Predictions Based on Threshold = .5000
-----
Prediction Success
-----
Sensitivity = actual 1s correctly predicted 46.748%
Specificity = actual 0s correctly predicted 78.886%
Positive predictive value = predicted 1s that were actual 1s 61.497%
Negative predictive value = predicted 0s that were actual 0s 67.250%
Correct prediction = actual 1s and 0s correctly predicted 65.417%

```

-----  
Prediction Failure

```

False pos. for true neg. = actual 0s predicted as 1s          21.114%
False neg. for true pos. = actual 1s predicted as 0s          53.252%
False pos. for predicted pos. = predicted 1s actual 0s       38.503%
False neg. for predicted neg. = predicted 0s actual 1s       32.750%
False predictions = actual 1s and 0s incorrectly predicted    34.583%
=====

```

Stata, SAS, and LIMDEP produce the same result. The likelihood ratio is  $128.6811 = -2 * [(-798.3122) - (-733.9716)]$ . While SAS reports  $AIC * N = 1,479.9433$ , LIMDEP returns an AIC of 1.2606 ( $= 1,479.943 / 1,174$ ). BIC (Schwarz IC) is  $1510.351 = 1.2865 * 1174$ . In order to compute marginal effects, add the `Marginal Effects` and `Means` subcommands to `Logit`. The following script computes marginal effects at the mean values of independent variables. Other parts in the output are skipped.

```

LOGIT, Lhs=TRUST;
      Rhs=ONE, EDUCATE, INCOME, AGE, MALE, WWW;
      Marginal Effects; Means$

```

```

+-----+-----+-----+-----+-----+-----+
|Variable| Coefficient | Standard Error | b/St. Er. | P[|Z|>z] | Elasticity|
+-----+-----+-----+-----+-----+
-----+Marginal effect for variable in probability
Constant|  -1.20446697  |   .11302276   |  -10.657   | .0000   |
EDUCATE |   .03663942   |   .00632491   |    5.793   | .0000   | 1.27598047
INCOME  |   .00733570   |   .00278319   |    2.636   | .0084   | .44211529
AGE     |   .00677169   |   .00117650   |    5.756   | .0000   | .68395424
-----+Marginal effect for dummy variable is P|1 - P|0.
MALE   |   .06213506   |   .03043408   |    2.042   | .0412   | .06845822
-----+Marginal effect for dummy variable is P|1 - P|0.
WWW    |   .12861867   |   .03653176   |    3.521   | .0004   | .24698361

```

```

+-----+-----+
| Marginal Effects for|
+-----+-----+
| Variable | All Obs. |
+-----+-----+
| ONE      | -1.20447 |
| EDUCATE  | .03664   |
| INCOME   | .00734   |
| AGE      | .00677   |
| MALE     | .06214   |
| WWW      | .12862   |
+-----+-----+

```

In order to compare marginal effects computed in Stata and LIMDEP, let us run `.prchange` again without reference points specified. `quietly` before a command run the command but suppresses the output. Stata and LIMDEP produce the same marginal effects (e.g., .0366 for education) and discrete changes (e.g., .1286 for WWW use). Notice that marginal effects and discrete changes vary depending on reference points used (compare with marginal effects in Section 2.2).

```

. quietly logit trust educate income age male www
. prchange

```

```

logit: Changes in Probabilities for trust

```

```

      min->max      0->1      -+1/2      --sd/2      MargEfct
educate   0.5259   0.0111   0.0366   0.0939   0.0366
income    0.1805   0.0057   0.0073   0.0454   0.0073

```

```

age      0.4428    0.0041    0.0068    0.0905    0.0068
male     0.0621    0.0621    0.0620    0.0309    0.0621
www      0.1286    0.1286    0.1331    0.0549    0.1338

          0          1
Pr(y|x)  0.5910  0.4090

      educate  income      age      male      www
x=    14.2428  24.6486  41.3075  .450596  .785349
sd_x=  2.56971  6.19427  13.4071  .497765  .410755

```

## 2.7 Binary Logit Model in SPSS

In SPSS, the `Logistic Regression` command fits the binary logit model. SPSS generates messy tables, which are often overwhelming beginners. The tables below are selected from the entire output.

```

LOGISTIC REGRESSION VARIABLES trust
  /METHOD=ENTER educate income age male www
  /CRITERIA=PIN(0.05) POUT(0.10) ITERATE(20) CUT(0.5).

```

**Model Summary**

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	1467.943 <sup>a</sup>	.104	.140

a. Estimation terminated at iteration number 4 because parameter estimates changed by less than .001.

**Variables in the Equation**

	B	S.E.	Wald	Df	Sig.	Exp(B)
Step 1 <sup>a</sup>						
educate	.152	.026	33.530	1	.000	1.164
income	.030	.012	6.920	1	.009	1.031
age	.028	.005	33.083	1	.000	1.028
male	.257	.126	4.165	1	.041	1.293
www	.554	.166	11.143	1	.001	1.740
Constant	-4.983	.478	108.511	1	.000	.007

a. Variable(s) entered on step 1: educate, income, age, male, www.

SPSS returns the same parameter estimates and their standard errors. Like SAS PROC LOGISTIC, SPSS reports  $-2 \times \text{Log-likelihood}$  ( $1,467.943 = -2 \times 733.9716$ ) and Wald statistics. P-values are listed under the label `Sig.` and factor changes in odds under `Exp(B)`. SPSS does not produce Pseudo  $R^2$ , AIC, Schwarz, and BIC.

Table 2.1 summarizes parameter estimates and goodness-of-fit measures of the binary logit model produced in Stata, SAS, R, and LIMDEP, excluding the output of PROC PROBIT and SPSS. Parameter estimates, their standard errors, and goodness-of-fit measures are identical except some rounding errors. Stata, R, and LIMDEP report z scores for hypothesis test, while PROC QLIM returns t scores and LOGISTIC, GENMOD, and PROBIT procedures conduct chi-square tests. PROC LOGISTIC and Stata `.logit` with `SPost` are general recommended.

**Table 2.1. Parameter Estimates and Goodness-of-fit of the Binary Logit Model**

	SAS			Stata	R	LIMDEP
	LOGISTIC	QLIM	GENMOD	.logit	glm()	Logit\$
Education	.1516 (.0262)	.1516 (.0262)	.1516 (.0262)	.1516 (.0262)	.1516 (.0262)	.1516 (.0262)
Family income	.0303 (.0115)	.0303 (.0115)	.0303 (.0115)	.0303 (.0115)	.0303 (.0115)	.0303 (.0115)
Age	.0280 (.0049)	.0280 (.0049)	.0280 (.0049)	.0280 (.0049)	.0280 (.0049)	.0280 (.0049)
Gender (male)	.2568 (.1258)	.2568 (.1258)	.2568 (.1258)	.2568 (.1258)	.2568 (.1258)	.2568 (.1258)
WWW use	.5537 (.1659)	.5537 (.1659)	.5537 (.1659)	.5537 (.1659)	.5537 (.1659)	.5537 (.1659)
Intercept	-4.9830 (.4784)	-4.9830 (.4784)	-4.9830 (.4784)	-4.9830 (.4784)	-4.9830 (.4784)	-4.9830 (.4784)
Log likelihood	-733.9716	-733.9716	-733.9716	-733.9716	-733.9716	-733.9716
Likelihood test	128.6811	128.68		128.68	128.6811	128.6811
Pseudo R <sup>2</sup>	.0806	.0806		.0806	.0806	.0806
AIC	1479.943	1480.	1479.9433	1479.943	1479.943	1479.944
BIC (Schwarz)	1510.352	1510.	1510.3523	1510.352		1510.352
H <sub>0</sub> test	Chi-square	t	Chi-square	z	z	z

\* PROC LOGISTIC and R report (-2\*Log-likelihood).

\*\* AIC\*N and BIC\*N in Stata and LIMDEP

### 3. Binary Probit Regression Model

The probit model is represented as  $\text{Prob}(y = 1 | x) = \Phi(x\beta)$ , where  $\Phi$  indicates the cumulative standard normal probability distribution function. Let us fit the binary probit model to see if there is substantial difference between binary logit and probit models.

#### 3.1 Binary Probit Model in Stata (.probit)

Stata `.probit` estimates the binary probit regression model. If you want to get robust standard errors, add the `robust` option to `.logit` and `.probit`. The logit and probit models produce almost similar goodness-of-fit measures but their parameter estimates are different each other.

```
. probit trust educate income age male www
```

```
Iteration 0: log likelihood = -798.31217
Iteration 1: log likelihood = -734.10951
Iteration 2: log likelihood = -733.99746
Iteration 3: log likelihood = -733.99746
```

```
Probit regression                               Number of obs =      1174
                                                LR chi2(5)      =    128.63
                                                Prob > chi2     =     0.0000
Log likelihood = -733.99746                    Pseudo R2      =     0.0806
```

trust	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
educate	.0907207	.0154349	5.88	0.000	.0604689 .1209725
income	.0185906	.0068681	2.71	0.007	.0051293 .0320519
age	.0173105	.0029496	5.87	0.000	.0115293 .0230916
male	.1593935	.0768819	2.07	0.038	.0087077 .3100793
www	.3417645	.0992156	3.44	0.001	.1473055 .5362235
_cons	-3.030053	.2786062	-10.88	0.000	-3.576111 -2.483995

Remember that the standard normal probability distribution and standard logistic distribution respectively have a unit variance and a variance of  $\pi^2/3$ . Therefore, a parameter estimate in a binary logit model is about 1.8138 ( $= \pi/\sqrt{3}$ ) larger than its corresponding coefficient in its probit counterpart. Long's suggestion is 1.7 (Long 1997: 48). For instance, the coefficient of education in the binary logit model is .1516, which is similar to .1542 ( $1.7 \cdot .0907$ ). See Cameron and Trivedi (2009: 451-452) for discussion on parameter estimates across models (OLS, binary logit, and binary probit model).

```
. di _pi/sqrt(3)*.0907207
.16454915
```

```
. di 1.7*.0907207
.15422519
```

Goodness-of-fit measures are very similar to those of the logit model. Log likelihoods are -733.972 and -733.997 and likelihood ratios are 128.681 and 128.629 in binary logit and probit models, respectively. They produce the same pseudo  $R^2$  of .0806.

```
. fitstat
```

```
Measures of Fit for probit of trust
```

Log-Lik Intercept Only:	-798.312	Log-Lik Full Model:	-733.997
D(1168):	1467.995	LR(5):	128.629
		Prob > LR:	0.000
McFadden's R2:	0.081	McFadden's Adj R2:	0.073
ML (Cox-Snell) R2:	0.104	Cragg-Uhler(Nagelkerke) R2:	0.140
McKelvey & Zavoina's R2:	0.166	Efron's R2:	0.105
Variance of y*:	1.199	Variance of error:	1.000
Count R2:	0.652	Adj Count R2:	0.171
AIC:	1.261	AIC*n:	1479.995
BIC:	-6787.630	BIC':	-93.289
BIC used by Stata:	1510.404	AIC used by Stata:	1479.995

In order to get standardized estimates, run SPost's `.listcoef` command. A coefficient is the impact of an independent variable for a unit increase in that variable, while the corresponding number under `bstdx` is the impact of the covariate for a standard deviation increase in that variable. For example, the x-standardized coefficient of education is .2331 (= .0907\*2.5697). Notice that factor changes in odds by definition are not available in a probit model.

```
. listcoef, help
```

```
probit (N=1174): Unstandardized and Standardized Estimates
```

```
Observed SD: .49361879
Latent SD: 1.0952088
```

trust	b	z	P> z	bStdX	bStdY	bStdXY	SDofX
educate	0.09072	5.878	0.000	0.2331	0.0828	0.2129	2.5697
income	0.01859	2.707	0.007	0.1152	0.0170	0.1051	6.1943
age	0.01731	5.869	0.000	0.2321	0.0158	0.2119	13.4071
male	0.15939	2.073	0.038	0.0793	0.1455	0.0724	0.4978
www	0.34176	3.445	0.001	0.1404	0.3121	0.1282	0.4108

```
b = raw coefficient
z = z-score for test of b=0
P>|z| = p-value for z-test
bStdX = x-standardized coefficient
bStdY = y-standardized coefficient
bStdXY = fully standardized coefficient
SDofX = standard deviation of X
```

The discrete change of a binary variable remains unchanged in the binary probit model, but the marginal effect of a continuous independent variable in the binary probit model is defined as,

$$\frac{\partial P(y=1|x)}{\partial x_c} = \phi(x\beta)\beta_c$$

where  $\phi$  denotes the standard normal probability density function.

You may compute marginal effects and discrete changes using either `.mfx` or SPost's `.prchange`. Marginal effects and discrete changes in the logit and probit models, despite different parameter estimates, are very similar (.0378 versus .0361 for education and .1329 versus .1320 for WWW use). Also two models return the similar predicted probability at the same reference points (.4753 versus .4747).

```
. mfx, at(mean educate=16 male=0 www=1)
```

```
Marginal effects after probit
```

```

y = Pr(trust) (predict)
  = .47469509
-----
variable |      dy/dx   Std. Err.    z    P>|z|   [      95% C.I.      ]      X
-----+-----
educate |   .0361195   .00681    5.30  0.000   .022774   .049465    16
income  |   .0074017   .00264    2.81  0.005   .002234   .012569   24.6486
age     |   .006892    .00118    5.83  0.000   .004574   .00921    41.3075
male*   |   .0635132   .03058    2.08  0.038   .003573   .123453    0
www*    |   .1320435   .0374     3.53  0.000   .058748   .205339    1
-----

```

(\*) dy/dx is for discrete change of dummy variable from 0 to 1

```
. prchange, x(educate=16 male=0 www=1) rest(mean)
```

```
probit: Changes in Probabilities for trust
```

	min->max	0->1	-+1/2	--sd/2	MargEfct
educate	0.5265	0.0123	0.0361	0.0926	0.0361
income	0.1916	0.0065	0.0074	0.0458	0.0074
age	0.4409	0.0051	0.0069	0.0922	0.0069
male	0.0635	0.0635	0.0634	0.0316	0.0635
www	0.1320	0.1320	0.1354	0.0558	0.1361

```

          0      1
Pr(y|x)  0.5253  0.4747

```

```

          educate  income      age      male      www
x=          16  24.6486  41.3075      0      1
sd_x=  2.56971  6.19427  13.4071  .497765  .410755

```

Similarly, `.prtab` and `.prvalue` report same predicted probabilities at the same reference points. Compare the following result with the output presented in Section 2.2.

```
. prtab male www, x(educate=16 male=0 www=1) rest(mean)
```

```
probit: Predicted probabilities of positive outcome for trust
```

```

-----
Gender |      WWW Use
      | Non-users  Users
-----+-----
Female |   0.3427   0.4747
Male   |   0.4029   0.5382
-----

```

```

          educate  income      age      male      www
x=          16  24.648637  41.307496      0      1

```

```
. prvalue, x(educate=16 male=0 www=1) rest(mean)
```

```
probit: Predictions for trust
```

```
Confidence intervals by delta method
```

```

          95% Conf. Interval
Pr(y=1|x):      0.4747  [ 0.4281,  0.5213]
Pr(y=0|x):      0.5253  [ 0.4787,  0.5719]

```

```

          educate  income      age      male      www
x=          16  24.648637  41.307496      0      1

```

Finally, let us draw a plot of predicted probabilities using `.prgen`. We are using the same reference points and same range of education (0 to 20) to get Figure 3.1. See Appendix for the Stata script used.

```
. quietly probit trust educate income age male www
```

```
. prgen educate, from(0) to(20) ncases(20) x(male=1 www=1) rest(mean) gen(Probit_age11)
probit: Predicted values as educate varies from 0 to 20.
      educate      income      age      male      www
x=    14.24276    24.648637   41.307496         1         1

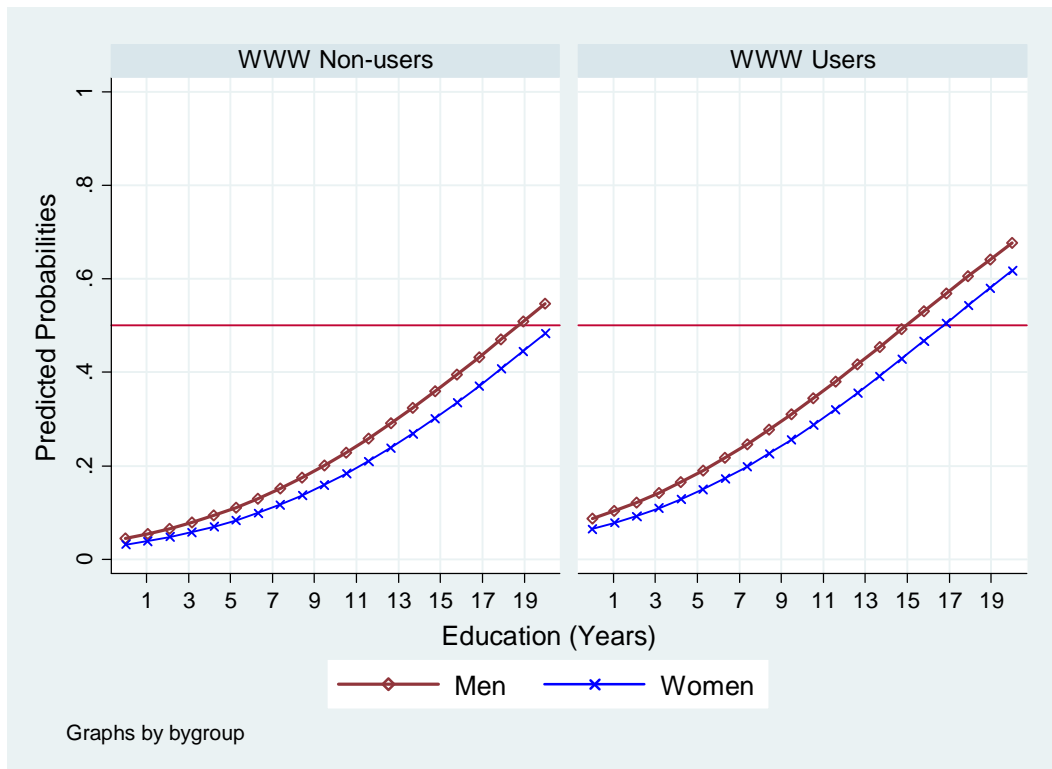
. prgen educate, from(0) to(20) ncases(20) x(male=1 www=0) rest(mean) gen(Probit_age10)
probit: Predicted values as educate varies from 0 to 20.
      educate      income      age      male      www
x=    14.24276    24.648637   41.307496         1         0

. prgen educate, from(0) to(20) ncases(20) x(male=0 www=1) rest(mean) gen(Probit_age01)
probit: Predicted values as educate varies from 0 to 20.
      educate      income      age      male      www
x=    14.24276    24.648637   41.307496         0         1

. prgen educate, from(0) to(20) ncases(20) x(male=0 www=0) rest(mean) gen(Probit_age00)
probit: Predicted values as educate varies from 0 to 20.
      educate      income      age      male      www
x=    14.24276    24.648637   41.307496         0         0
```

Compare Figure 2.1 and 3.1 to find they are almost identical. This finding is not surprising at all because predicted probabilities, marginal effects, and discrete changes are very similar in binary logit and probit models, although two models produce different parameter estimates and standard errors.

Figure 3.1 Predicted Probabilities of Trusting Most People (Binary Probit Model)



### 3.2 Binary Probit Model in SAS: PROC PROBIT and PROC LOGISTIC

PROBIT and LOGISTIC procedures estimate the binary probit model. Keep in mind that the coefficients of PROC PROBIT has opposite signs. Stata and SAS produce the same result.

```
PROC PROBIT DATA = masil.gss_cdvm;
MODEL trust = educate income age male www;
RUN;
```

The Probit Procedure

Model Information

Data Set	MASIL.GSS_CDVM	
Dependent Variable	trust	trust
Number of Observations	1174	
Name of Distribution	Normal	
Log Likelihood	-733.9974633	

Number of Observations Read	1174
Number of Observations Used	1174

Class Level Information

Name	Levels	Values
trust	2	0 1

Response Profile

Ordered Value	trust	Total Frequency
1	0	682
2	1	492

PROC PROBIT is modeling the probabilities of levels of trust having LOWER Ordered Values in the response profile table.

Algorithm converged.

Type III Analysis of Effects

Effect	DF	Wald	
		Chi-Square	Pr > ChiSq
educate	1	34.5467	<.0001
income	1	7.3266	0.0068
age	1	34.4417	<.0001
male	1	4.2983	0.0382

www	1	11.8657	0.0006
-----	---	---------	--------

## Analysis of Maximum Likelihood Parameter Estimates

Parameter	DF	Estimate	Standard Error	95% Confidence Limits		Chi-Square	Pr > ChiSq
Intercept	1	3.0300	0.2786	2.4840	3.5761	118.28	<.0001
educate	1	-0.0907	0.0154	-0.1210	-0.0605	34.55	<.0001
income	1	-0.0186	0.0069	-0.0321	-0.0051	7.33	0.0068
age	1	-0.0173	0.0029	-0.0231	-0.0115	34.44	<.0001
male	1	-0.1594	0.0769	-0.3101	-0.0087	4.30	0.0382
www	1	-0.3418	0.0992	-0.5362	-0.1473	11.87	0.0006

PROC LOGISTIC requires a normal probability distribution as a link function (/LINK=PROBIT or /LINK=NORMIT) to fit a binary probit model. McFadden's pseudo  $R^2$  is  $.0806=1-(.1467.995/1596.624)$ . OUTEST stores parameter estimates into a SAS data set *masil.bpm*, which will be used when computing marginal effects later.

```
PROC LOGISTIC DATA = masil.gss_cdvm DESC OUTEST=masil.bpm;
MODEL trust = educate income age male www /LINK=PROBIT;
RUN;
```

## The LOGISTIC Procedure

## Model Information

Data Set	MASIL.GSS_CDVM	
Response Variable	trust	trust
Number of Response Levels	2	
Model	binary probit	
Optimization Technique	Fisher's scoring	

Number of Observations Read	1174
Number of Observations Used	1174

## Response Profile

Ordered Value	trust	Total Frequency
1	1	492
2	0	682

Probability modeled is trust=1.

## Model Convergence Status

Convergence criterion (GCONV=1E-8) satisfied.

## Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	1598.624	1479.995
SC	1603.693	1510.404
-2 Log L	1596.624	1467.995

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	128.6294	5	<.0001
Score	121.5344	5	<.0001
Wald	118.2980	5	<.0001

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept	1	-3.0298	0.2796	117.4048	<.0001
educate	1	0.0907	0.0158	32.9144	<.0001
income	1	0.0186	0.00682	7.4273	0.0064
age	1	0.0173	0.00295	34.3163	<.0001
male	1	0.1594	0.0769	4.2979	0.0382
www	1	0.3418	0.0995	11.7914	0.0006

Association of Predicted Probabilities and Observed Responses

Percent Concordant	68.4	Somers' D	0.371
Percent Discordant	31.3	Gamma	0.372
Percent Tied	0.4	Tau-a	0.181
Pairs	335544	c	0.686

Stata, PROC LOGISTIC, and PROC PROBIT share same parameter estimates, but PROC LOGISTIC reports slightly different standard errors (e.g., .0158 versus .0154 for education). The following script fits the same model using /LINK=NORMIT and stores the SAS output in a HTML file `c:\temp\sas\logit.html` using ODS.

```
ODS HTML FILE='c:\temp\sas\probit.html';
PROC LOGISTIC DATA = masil.gss_cdvm DESC;
    MODEL trust(EVENT='1') = educate income age male www /LINK=NORMIT;
RUN;
ODS HTML CLOSE;
```

Let us compute marginal effects using SAS/IML. Remember we store parameter estimates in `masil.bpm`. The following SAS script highlights the only parts different from the PROC IML in Section 2.3. `PROBNORM()`=`CDF('NORMAL')` and `PDF('NORMAL')` are respectively CDF and PDF of the standard normal distribution.

```

PROC IML;
USE masil.bpm; /* get a row vector of parameter estimates */
READ ALL VAR{Intercept educate income age male www} INTO bHat;
K=NCOL(bHat); /* get the number of regressors */
...

prob = PROBNORM(xb); /* compute a predicted probability */
...

margin = PDF('NORMAL', xb, 0, 1) * T(bHat); /* compute marginal effects */
marginSD = PDF('NORMAL', xb, 0, 1) * T(bHat # sdX);
...

QUIT; /* terminate PROC IML */

```

The predicted probability that female WWW users will trust people is 47.47 percent, holding other covariates at their means. Calculated marginal effects are the same as what `.prchange` returned in Section 3.1.

referX					prob
1	16	24.648637	41.307496	0	1 0.4746975

	result				
	b	MargEffect	MargEffect(SD)	Mean of X	SD of X
educate	0.0907156	0.0361175	0.0928116	14.24276	2.5697123
income	0.0185849	0.0073994	0.0458338	24.648637	6.1942699
age	0.0173094	0.0068915	0.0923958	41.307496	13.407127
male	0.1593898	0.0634594	0.0315879	0.4505963	0.4977653
www	0.3417757	0.1360745	0.0558932	0.7853492	0.4107548

### 3.3 Binary Probit Model in SAS: PROC QLIM and PROC GENMOD

PROC QLIM provides various goodness-of-fit statistics. The `DIST=NORMAL` option below indicates the normal probability distribution to be used in estimation. Compared to PROC LOGISTIC, PROC QLIM reports same parameter estimates and goodness-of-fit statistics but slightly different standard errors.

```

PROC QLIM DATA=masil.gss_cdv;
MODEL trust = educate income age male www /DISCRETE (DIST=NORMAL);
RUN;

```

The QLIM Procedure

Discrete Response Profile of trust

Index	Value	Frequency	Percent
1	0	682	58.09
2	1	492	41.91

Model Fit Summary

Number of Endogenous Variables	1
Endogenous Variable	trust
Number of Observations	1174
Log Likelihood	-733.99746
Maximum Absolute Gradient	0.00200
Number of Iterations	11
Optimization Method	Quasi-Newton
AIC	1480
Schwarz Criterion	1510

## Goodness-of-Fit Measures

Measure	Value	Formula
Likelihood Ratio (R)	128.63	$2 * (\text{LogL} - \text{LogL0})$
Upper Bound of R (U)	1596.6	$- 2 * \text{LogL0}$
Aldrich-Nelson	0.0987	$R / (R+N)$
Cragg-Uhler 1	0.1038	$1 - \exp(-R/N)$
Cragg-Uhler 2	0.1396	$(1 - \exp(-R/N)) / (1 - \exp(-U/N))$
Estrella	0.1079	$1 - (1 - R/U)^{(U/N)}$
Adjusted Estrella	0.098	$1 - ((\text{LogL} - K) / \text{LogL0})^{(-2/N * \text{LogL0})}$
McFadden's LRI	0.0806	$R / U$
Veall-Zimmermann	0.1714	$(R * (U+N)) / (U * (R+N))$
McKelvey-Zavoina	0.1662	

N = # of observations, K = # of regressors

Algorithm converged.

## Parameter Estimates

Parameter	DF	Estimate	Standard Error	t Value	Approx Pr >  t
Intercept	1	-3.030053	0.278616	-10.88	<.0001
educate	1	0.090721	0.015435	5.88	<.0001
income	1	0.018591	0.006868	2.71	0.0068
age	1	0.017310	0.002950	5.87	<.0001
male	1	0.159393	0.076882	2.07	0.0382
www	1	0.341764	0.099215	3.44	0.0006

PROC GENMOD estimates the binary probit model using the /DIST=BINOMIAL and /LINK=PROBIT options in the MODEL statement. Again, DESC uses a larger value as a positive event (success). PROC QLIM and PROC GENMOD return same parameter estimates, standard errors, and goodness-of-fit measures.

```
PROC GENMOD DATA = masil.gss_cdvms DESC;
  MODEL trust = educate income age male www /DIST=BINOMIAL LINK=PROBIT;
RUN;
```

The GENMOD Procedure

Model Information

```

Data Set           MASIL.GSS_CDVM
Distribution        Binomial
Link Function       Probit
Dependent Variable trust   trust

```

```

Number of Observations Read  1174
Number of Observations Used  1174
Number of Events              492
Number of Trials              1174

```

## Response Profile

Ordered Value	trust	Total Frequency
1	1	492
2	0	682

PROC GENMOD is modeling the probability that trust='1'.

## Criteria For Assessing Goodness Of Fit

Criterion	DF	Value	Value/DF
Log Likelihood		-733.9975	
Full Log Likelihood		-733.9975	
AIC (smaller is better)		1479.9949	
AICC (smaller is better)		1480.0669	
BIC (smaller is better)		1510.4040	

Algorithm converged.

## Analysis Of Maximum Likelihood Parameter Estimates

Parameter	DF	Estimate	Standard Error	Wald 95% Confidence Limits		Wald Chi-Square	Pr > ChiSq
Intercept	1	-3.0301	0.2786	-3.5761	-2.4840	118.28	<.0001
educate	1	0.0907	0.0154	0.0605	0.1210	34.55	<.0001
income	1	0.0186	0.0069	0.0051	0.0321	7.33	0.0068
age	1	0.0173	0.0029	0.0115	0.0231	34.44	<.0001
male	1	0.1594	0.0769	0.0087	0.3101	4.30	0.0382
www	1	0.3418	0.0992	0.1473	0.5362	11.87	0.0006
Scale	0	1.0000	0.0000	1.0000	1.0000		

NOTE: The scale parameter was held fixed.

### 3.4 Binary Probit Model in R

The `glm()` function fits the binary probit model with `family=binomial(link="probit")`.

```

> bpm<-glm(trust~educate+income+age+male+www, data=df, family=binomial(link="probit"))

> summary(bpm)

Call:
glm(formula = trust ~ educate + income + age + male + www, family = binomial(link = "probit"),
    data = df)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.8299 -1.0033 -0.6756  1.1496  2.1831

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept) -3.030037   0.279632 -10.836 < 2e-16 ***
educate      0.090719   0.015812  5.737 9.63e-09 ***
income      0.018591   0.006820  2.726 0.006410 **
age         0.017311   0.002955  5.858 4.68e-09 ***
male       0.159394   0.076884  2.073 0.038157 *
www        0.341768   0.099532  3.434 0.000595 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 1596.6  on 1173  degrees of freedom
Residual deviance: 1468.0  on 1168  degrees of freedom
AIC: 1480

Number of Fisher Scoring iterations: 4

```

Parameter estimates are same across Stata, PROC LOGISTIC, and PROC QLIM. R and PROC LOGISTIC share same standard errors, which are slightly different from those of Stata, PROC QLIM, PROC GENMOD, and PROC PROBIT. Let us conduct the likelihood ratio test using deviances of the null and full models. The pseudo  $R^2$  .0806 is also computed from the two deviances.

```

> bpm$deviance/-2
[1] -733.9975

> AIC(bpm)
[1] 1479.995

> LRtest<-bpm$null.deviance-blm$deviance
> LRtest
[1] 128.6811

> dchisq(LRtest, bpm$df.null - bpm$df.residual)
[1] 2.214737e-26

> 1-bpm$deviance/bpm$null.deviance # McFadden's pseudo R square
[1] 0.08056336

```

In order to get the predicted probability, use the same script except for the cumulative standard normal distribution function (CDF) `pnorm()`. The predicted probability is 47.47 percent at the same reference points.

```

> bHat<-coef(bpm) # vector of parameter estimates
> K<-length(bHat) # the number of regressors

> referX<-c(1, 16, mean(income), mean(age), 0, 1)
> xb<-bHat %*% referX # element by element product
> prob<-pnorm(xb)
> prob
[1,]

```

```
[1,] 0.4746947
```

When calculating marginal effects in the binary probit model, use the standard normal probability density function (PDF) `dnorm()`. The following `for()` loop sets two reference points of 0 and 1 and computes the difference of the two predicted probabilities.

```
> margin<-cbind(bHat, dnorm(xb)*bHat, dnorm(xb)*bHat*sdX, meanX, sdX)

> for (i in c(5, 6)) { # locations of binary variables
+   referX0<-matrix(referX)
+   referX1<-matrix(referX)
+   referX0[i,1]<-0
+   referX1[i,1]<-1
+
+   xb0<-bHat %*% referX0
+   xb1<-bHat %*% referX1
+
+   dChange<-pnorm(xb1)-pnorm(xb0)
+   margEffect[i,2]<-dChange # replace the marginal effect with the discrete change
+ }
>
> margEffect<-margEffect[2:K,]
> colnames(margEffect)<-c("b", "MargEffect", "MargEffect(SD)", "Mean of X", "SD of X")
> margEffect
```

	b	MargEffect	MargEffect(SD)	Mean of X	SD of X
educate	0.09071919	0.036118888	0.09281515	14.2427598	2.5697123
income	0.01859065	0.007401671	0.04584795	24.6486371	6.1942699
age	0.01731051	0.006891997	0.09240188	41.3074957	13.4071272
male	0.15939356	0.063513240	0.03158862	0.4505963	0.4977653
www	0.34176814	0.132044777	0.05589197	0.7853492	0.4107548

Compare above marginal effects with the results of `.prchange` in Section 3.1 and PROC IML in Section 3.2.

### 3.5 Binary Probit Model in LIMDEP (Probit\$)

In LIMDEP, the `Probit$` command estimates various probit models. Do not forget to include the ONE for the intercept. Stata, SAS, and LIMDEP produce the same result.

```
PROBIT;Lhs=TRUST;
  Rhs=ONE, EDUCATE, INCOME, AGE, MALE, WWW;
  Marginal Effects; Means$
```

```
Normal exit from iterations. Exit status=0.
```

```
| Binomial Probit Model |
| Maximum Likelihood Estimates |
| Model estimated: Sep 09, 2009 at 11:41:52PM. |
| Dependent variable | TRUST |
| Weighting variable | None |
| Number of observations | 1174 |
| Iterations completed | 5 |
| Log likelihood function | -733.9975 |
| Number of parameters | 6 |
| Info. Criterion: AIC = | 1.26064 |
| Finite Sample: AIC = | 1.26070 |
| Info. Criterion: BIC = | 1.28655 |
| Info. Criterion:HQIC = | 1.27041 |
| Restricted log likelihood | -798.3122 |
| McFadden Pseudo R-squared | .0805634 |
| Chi squared | 128.6294 |
| Degrees of freedom | 5 |
| Prob[ChiSqd > value] = | .0000000 |
| Hosmer-Lemeshow chi-squared = | 4.81557 |
```

| P-value= .77709 with deg.fr. = 8 |

Variable	Coefficient	Standard Error	b/St.Er.	P[ Z >z]	Mean of X
Constant	-3.03005313	.27860620	-10.876	.0000	
EDUCATE	.09072070	.01543488	5.878	.0000	14.2427598
INCOME	.01859061	.00686814	2.707	.0068	24.6486371
AGE	.01731045	.00294962	5.869	.0000	41.3074957
MALE	.15939348	.07688194	2.073	.0382	.45059625
WWW	.34176450	.09921561	3.445	.0006	.78534923

-----ves of E[y] = F[\*] with |  
 | respect to the vector of characteristics. |  
 | They are computed at the means of the Xs. |  
 | Observations used for means are All Obs. |

Variable	Standard Error	b/St.Er.	P[ Z >z]	Elasticity
Constant	-.58627711	.01519985	-38.571	.0000
EDUCATE	.03529223	.00600827	5.874	.0000
INCOME	.00723213	.00266928	2.709	.0067
AGE	.00673413	.00114709	5.871	.0000
-----+Marginal effect for dummy variable is P 1 - P 0.				
MALE	.06205251	-.02991770	2.074	.0381
-----+Marginal effect for dummy variable is P 1 - P 0.				
WWW	.12889554	-.03589934	3.590	.0003

-----odel |  
 | Probit model for variable TRUST |  
 +-----0 |  
 | N = 1174 N0= 682 N1= 492 |  
 | LogL= -733.997 LogL0= -798.312 |  
 | Estrella = 1-(L/L0)^(-2L0/n) = .10795 |  
 +-----+ |  

	.10456	.08056	.56389
Cramer	.10440	.17135	.10378

Criteria	1.26064	1.28655
----------	---------	---------

-----ed value is |  
 | 1 when probability is greater than .500000, 0 otherwise. |  
 | Note, column or row total percentages may not sum to |  
 | 100% because of rounding. Percentages are of full sample. |  
 +-----+ |

Value	0	1	Total Actual
1	263 ( 22.4%)	229 ( 19.5%)	492 ( 41.9%)

=====5000

Sensitivity = actual 1s correctly predicted	46.545%
Specificity = actual 0s correctly predicted	78.739%
Positive predictive value = predicted 1s that were actual 1s	61.230%
Negative predictive value = predicted 0s that were actual 0s	67.125%
Correct prediction = actual 1s and 0s correctly predicted	65.247%

Prediction Failure

False pos. for true neg. = actual 0s predicted as 1s	21.261%
False neg. for true pos. = actual 1s predicted as 0s	53.455%
False pos. for predicted pos. = predicted 1s actual 0s	38.770%
False neg. for predicted neg. = predicted 0s actual 1s	32.875%
False predictions = actual 1s and 0s incorrectly predicted	34.753%

Compare marginal effects above with the following that .prchange computed at the means of all independent variables.

. prchange

probit: Changes in Probabilities for trust

	min->max	0->1	-+1/2	-+sd/2	MargEfct
educate	0.5262	0.0123	0.0353	0.0905	0.0353
income	0.1816	0.0059	0.0072	0.0448	0.0072
age	0.4435	0.0045	0.0067	0.0901	0.0067
male	0.0621	0.0621	0.0619	0.0309	0.0620
www	0.1289	0.1289	0.1323	0.0546	0.1330

Pr(y|x)            0            1  
 0.5888   0.4112

educate    income            age            male            www  
 x=    14.2428   24.6486   41.3075   .450596   .785349  
 sd\_x=   2.56971   6.19427   13.4071   .497765   .410755

### 3.6 Binary Probit Model in SPSS

SPSS has the `PROBIT` command to fit the binary probit model. This command requires an additional variable (e.g., *n* in the following example) with constant 1. If you want to use GUI menu (point-and-click), include *n* in `Total Observed:` and independent variables in `Covariate(s)` of a dialog box `Probit Analysis`.

```
COMPUTE n=1.
PROBIT trust OF n WITH educate income age male www
  /LOG NONE
  /MODEL PROBIT
  /PRINT FREQ
  /CRITERIA ITERATE(20) STEPLIMIT(.1).
```

The following tables are selected from messy SPSS output. Stata, SAS, LIMDEP, SPSS produces same parameter estimates and goodness-of-fit measures.

Parameter Estimates

Parameter	Estimate	Std. Error	Z	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
PROBITa educate	.091	.015	5.878	.000	.060	.121
income	.019	.007	2.707	.007	.005	.032
age	.017	.003	5.869	.000	.012	.023
male	.159	.077	2.073	.038	.009	.310
www	.342	.099	3.445	.001	.147	.536
Intercept	-3.030	.279	-10.876	.000	-3.309	-2.751

a. PROBIT model:  $PROBIT(p) = \text{Intercept} + BX$

Chi-Square Tests

	Chi-Square	Dfa	Sig.
PROBIT Pearson Goodness-of-Fit Test	1174.457	1168	.442

## Chi-Square Tests

		Chi-Square	Dfa	Sig.
PROBIT	Pearson Goodness-of-Fit Test	1174.457	1168	.442

a. Statistics based on individual cases differ from statistics based on aggregated cases.

The `probit` command also fits the binary logit model. The following command reports z scores instead of Wald statistics and does not report factor changes of the odds. The output is skipped.

```
PROBIT trust OF n WITH educate income age male www
  /LOG NONE
  /MODEL LOGIT
  /PRINT FREQ
  /CRITERIA ITERATE(20) STEPLIMIT(.1).
```

Table 3.1 summarizes parameter estimates and goodness-of-fit statistics produced in SAS, Stata, R, and LIMDEP. Parameter estimates are the same across software packages, but standard errors in PROC LOGISTIC and R are slightly different from those computed in other software packages (i.e., PROC QLIM, PROC GENMOD, PROC PROBIT, Stata, LIMDEP, and SPSS). I would recommend PROC LOGISTIC and Stata for the binary probit model.

**Table 3.1 Parameter Estimates and Goodness-of-fit of the Binary Probit Model**

	SAS			Stata	R	LIMDEP
	LOGISTIC	QLIM	GENMOD	.probit	glm()	Probit\$
Education	.0907 (.0158)	.0907 (.0154)	.0907 (.0154)	.0907 (.0154)	.0907 (.0158)	.0907 (.0154)
Family income	.0186 (.0068)	.0186 (.0069)	.0186 (.0069)	.0186 (.0069)	.0186 (.0068)	.0186 (.0069)
Age	.0173 (.0030)	.0173 (.0030)	.0173 (.0029)	.0173 (.0029)	.0173 (.0030)	.0173 (.0029)
Gender (male)	.1594 (.0769)	.1594 (.0769)	.1594 (.0769)	.1594 (.0769)	.1594 (.0769)	.1594 (.0769)
WWW use	.3418 (.0995)	.3418 (.0992)	.3418 (.0992)	.3418 (.0992)	.3418 (.0995)	.3418 (.0992)
Intercept	-3.0298 (.2796)	-3.0301 (.2786)	-3.0301 (.2786)	-3.0301 (.2786)	-3.0300 (.2796)	-3.0301 (.2786)
Log likelihood	-733.9975	-733.9975	-733.9975	-733.9975	-733.9975	-733.9975
Likelihood test	128.629	128.63		128.63	128.6811	128.6294
Pseudo R <sup>2</sup>	.0806	.0806		.0806	.0806	.0806
AIC	1479.995	1480.	1479.9949	1479.995	1749.995	1749.9914
BIC (Schwarz)	1510.404	1510.	1510.4040	1510.404		1510.4097
H <sub>0</sub> test	Chi-square	t	Chi-square	z	z	z

\* PROC LOGISTIC and R reports (-2\*Log-likelihood).

\*\* AIC\*N and BIC\*N in Stata and LIMDEP

## 4. Bivariate Probit Regression Models

Bivariate probit regression models have two equations for two binary dependent variables. This chapter explains how to fit the bivariate probit model and the recursive bivariate regression model with an endogenous variable. The recursive bivariate probit model is formulated as (Maddala 1983:122-123; Greene 2003:715-716),

$$\begin{aligned} y_1^* &= x_1' \beta_1 + y_2 \gamma + \varepsilon_1, & y_1 &= 1 \text{ if } y_1^* > 0, 0 \text{ otherwise,} \\ y_2^* &= x_2' \beta_2 + \varepsilon_2, & y_2 &= 1 \text{ if } y_2^* > 0, 0 \text{ otherwise,} \end{aligned}$$

where  $y_1$  is a binary dependent variable of interest in equation 1,  $y_2$  is a binary dependent variable of equation 2 that is included in the first equation as an endogenous variable, and  $x_1$  and  $x_2$  are the regressor vectors of two regression equations. A typical bivariate probit model does not include  $y_2 \gamma$  in the first equation. Disturbances of two equations are assumed to be “independent, identically distributed” and follow the bivariate standard normal probability distribution with their correlation coefficient  $\rho$ .

$$\phi_2(\varepsilon_1, \varepsilon_2, \rho) = \frac{1}{2\pi\sqrt{1-\rho^2}} \exp\left[\frac{-1}{2(1-\rho^2)}(\varepsilon_1^2 + \varepsilon_2^2 - 2\rho\varepsilon_1\varepsilon_2)\right]$$

Here we consider a model, where social trust and WWW use are jointly determined. Stata, SAS, and LIMDEP can fit bivariate probit models.

### 4.1 Bivariate Probit Model in Stata (.biprobit)

In Stata, `.biprobit` estimates bivariate probit models. If both equations have the same specification, you may list two dependent variables followed by covariates. If not, you need to specify equations individually, in each of which a binary variable and independent variables separated by an equal sign. The following two commands fit exactly the same model.

```
. quietly biprobit trust www educate income age male // or
. biprobit (trust = educate income age male) (www = educate income age male)
```

Fitting comparison equation 1:

```
Iteration 0:  log likelihood = -798.31217
Iteration 1:  log likelihood = -740.16976
Iteration 2:  log likelihood = -740.02303
Iteration 3:  log likelihood = -740.02303
```

Fitting comparison equation 2:

```
Iteration 0:  log likelihood = -610.5431
Iteration 1:  log likelihood = -564.86129
Iteration 2:  log likelihood = -564.36806
Iteration 3:  log likelihood = -564.36805
```

```
Comparison:  log likelihood = -1304.3911
```

Fitting full model:

```
Iteration 0:  log likelihood = -1304.3911
```

```
Iteration 1: log likelihood = -1297.8302
Iteration 2: log likelihood = -1297.8205
Iteration 3: log likelihood = -1297.8205
```

```
Bivariate probit regression      Number of obs   =      1174
                                Wald chi2(8)      =      185.87
Log likelihood = -1297.8205     Prob > chi2     =      0.0000
```

	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
-----						
trust						
educate	.1028598	.0150584	6.83	0.000	.073346	.1323737
income	.0202876	.0068117	2.98	0.003	.0069369	.0336384
age	.0161267	.0029175	5.53	0.000	.0104085	.021845
male	.165699	.0766088	2.16	0.031	.0155486	.3158495
_cons	-2.926968	.2750501	-10.64	0.000	-3.466056	-2.38788
-----						
www						
educate	.1478252	.0180092	8.21	0.000	.1125278	.1831225
income	.0188763	.0065797	2.87	0.004	.0059803	.0317723
age	-.0103983	.0031951	-3.25	0.001	-.0166606	-.0041361
male	.0776235	.0864866	0.90	0.369	-.091887	.247134
_cons	-1.317766	.289774	-4.55	0.000	-1.885713	-.7498197
-----						
/athrho	.2035694	.0565478	3.60	0.000	.0927378	.314401
-----						
rho	.2008033	.0542676			.0924729	.3044355
-----						

```
Likelihood-ratio test of rho=0: chi2(1) = 13.1412 Prob > chi2 = 0.0003
```

This model fits the data well ( $\chi^2=185.87$ ,  $p<.0000$ ). `.fitstat` and other `SPost` commands do not work with this model. Instead, `.estat` returns AIC 2,618 and BIC 2,673, respectively.

```
. estat ic
```

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
.	1174	.	-1297.82	11	2617.641	2673.391

```
Note: N=Obs used in calculating BIC; see [R] BIC note
```

We can compute marginal effects and conditional marginal effects using `predict(pmarg1)` and `predict(pcond1)`, respectively. If the correlation of disturbances of two equations is zero, they should be identical. Since the likelihood ratio test above rejects the null hypothesis of zero correlation ( $\chi^2=13.1412$ ,  $p<.0003$ ), marginal effects and conditional marginal effects here are different even at the same reference points.

```
. mfx, predict(pcond1) at(mean educate=16 male=0)
```

```
Marginal effects after biprobit
  y = Pr(trust=1|www=1) (predict, pcond1)
  = .4744549
```

variable	dy/dx	Std. Err.	z	P> z	[ 95% C.I. ]		X
educate	.0371474	.00613	6.06	0.000	.025124	.049171	16
income	.0076112	.00272	2.80	0.005	.002278	.012944	24.6486
age	.006753	.00117	5.79	0.000	.004467	.009039	41.3075
male*	.0643811	.03051	2.11	0.035	.004592	.124171	0

```
(*) dy/dx is for discrete change of dummy variable from 0 to 1
```

```
. mfx, predict(pmarg1) at(mean educate=16 male=0)
```

Marginal effects after biprobit

y = Pr(trust=1) (predict, pmargl)  
= .45422459

variable	dy/dx	Std. Err.	z	P> z	[	95% C.I.	]	X
educate	.0407647	.00609	6.69	0.000	.028822	.052708		16
income	.0080402	.0027	2.98	0.003	.002752	.013329		24.6486
age	.0063912	.00116	5.53	0.000	.004127	.008655		41.3075
male*	.0659948	.03045	2.17	0.030	.006316	.125674		0

(\*) dy/dx is for discrete change of dummy variable from 0 to 1

## 4.2 Recursive Bivariate Probit Model in Stata (.biprobit)

What if WWW use influences social trust directly? In other words, WWW use is the dependent variable in the second equation and is also included in the first equation as an endogenous variable. This is a recursive bivariate probit model, which is explained in Maddala (1983) and Greene (1996, 2003). Since the two equations have different specifications, they should be provided separately in parentheses after the .biprobit command. Check the model name Seemingly unrelated bivariate probit in the following output.

```
. biprobit (trust = educate income age male www) (www = educate income age male)
```

Fitting comparison equation 1:

```
Iteration 0: log likelihood = -798.31217
Iteration 1: log likelihood = -734.10951
Iteration 2: log likelihood = -733.99746
Iteration 3: log likelihood = -733.99746
```

Fitting comparison equation 2:

```
Iteration 0: log likelihood = -610.5431
Iteration 1: log likelihood = -564.86129
Iteration 2: log likelihood = -564.36806
Iteration 3: log likelihood = -564.36805
```

Comparison: log likelihood = -1298.3655

Fitting full model:

```
Iteration 0: log likelihood = -1298.3655
Iteration 1: log likelihood = -1298.2982
Iteration 2: log likelihood = -1297.3043
Iteration 3: log likelihood = -1297.3008
Iteration 4: log likelihood = -1297.3007
```

```
Seemingly unrelated bivariate probit          Number of obs   =       1174
Log likelihood = -1297.3007                  Wald chi2(9)     =       194.40
                                              Prob > chi2      =       0.0000
```

	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
trust					
educate	.1228844	.0197756	6.21	0.000	.084125 .1616437
income	.0225769	.0066392	3.40	0.001	.0095643 .0355894
age	.0126723	.004382	2.89	0.004	.0040837 .021261
male	.1682476	.0743747	2.26	0.024	.0224759 .3140193
www	-.7178395	.5729155	-1.25	0.210	-1.840733 .4050543
_cons	-2.531195	.4938755	-5.13	0.000	-3.499174 -1.563217
www					
educate	.1510947	.0182167	8.29	0.000	.1153906 .1867988
income	.0188034	.0065301	2.88	0.004	.0060047 .0316021

age		-.0101814	.0031937	-3.19	0.001	-.0164409	-.0039219
male		.0663948	.086608	0.77	0.443	-.1033538	.2361435
_cons		-1.365747	.2928927	-4.66	0.000	-1.939807	-.7916883
-----							
/athrho		.6719729	.4621132	1.45	0.146	-.2337523	1.577698
-----							
rho		.5862762	.3032758			-.2295859	.9182416
-----							
Likelihood-ratio test of rho=0:				chi2(1) =	2.12962	Prob > chi2 =	0.1445

This model also fits the data well ( $\chi^2=194.40$ ,  $p<.0000$ ) and most individual parameters are statistically significant at the .05 level. AIC and BIC are 2,619 and 2,679, respectively.

```
. estat ic
```

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
.	1174	.	-1297.301	12	2618.601	2679.419

Note: N=Obs used in calculating BIC; see [R] BIC note

However, the LR test ( $\chi^2=2.1296$ ) suggests that two disturbances are not significantly correlated. The estimated correlation .5863 is far away from zero but is not statistically discernable ( $p<.1445$ ). Therefore, social trust and WWW use may not be jointly determined; each equation may need to be estimated separately or may be analyzed in the bivariate probit model. The binary probit model for WWW use is as follows.

```
. probit www educate income age male
```

```
Iteration 0: log likelihood = -610.5431
Iteration 1: log likelihood = -564.86129
Iteration 2: log likelihood = -564.36806
Iteration 3: log likelihood = -564.36805
```

```
Probit regression                               Number of obs   =    1174
                                                LR chi2(4)      =    92.35
                                                Prob > chi2     =    0.0000
Log likelihood = -564.36805                    Pseudo R2      =    0.0756
```

www	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
educate	.1454532	.0178746	8.14	0.000	.1104197 .1804868
income	.0189197	.0065902	2.87	0.004	.0060031 .0318362
age	-.0103946	.0032009	-3.25	0.001	-.0166682 -.004121
male	.08164	.0865442	0.94	0.346	-.0879834 .2512635
_cons	-1.288283	.2885836	-4.46	0.000	-1.853896 -.7226694

In the recursive bivariate probit model, conditional marginal effects make more sense than typical marginal effects. The predicted probability that citizens trust most people is 47.21 percent at the reference points, given they use WWW:  $\text{pr}(\text{trust}=1 | \text{www}=1) = .4721$ .

```
. quietly biprobit (trust = educate income age male www) (www = educate income age male)
```

```
. mfx, predict(pcond1) at(mean educate=16 male=0 www=1)
```

```
Marginal effects after biprobit
      y = Pr(trust=1|www=1) (predict, pcond1)
      = .47208977
```

variable	dy/dx	Std. Err.	z	P> z	[ 95% C.I. ]	X
----------	-------	-----------	---	------	--------------	---

	educate	income	age	male	www	
educate	.0394964	.00635	6.22	0.000	.027053	.05194
income	.0079921	.00266	3.01	0.003	.002786	.013198
age	.0061891	.00132	4.67	0.000	.003592	.008786
male*	.065738	.02987	2.20	0.028	.007193	.124284
www*	-.2858939	.21383	-1.34	0.181	-.704984	.133196

(\*) dy/dx is for discrete change of dummy variable from 0 to 1

Stata `.mfx` does not report direct and indirect effects but returns the sum of the two effects. When combining direct and indirect effects, for an additional increase in education from the 16 years, the conditional predicted probability of trusting people will increase by 3.95 percent, holding all other variables constant at their reference points.

The following Stata script illustrates how to manually compute direct and indirect effects of covariates. See the Stata script in Appendix for entire steps of computation. Beginners may skip this part and take a look at the result table only. Find the predicted probability of .4721 in the middle of the output. See Greene (1996, 2007) for related formulas.

```
. quietly biprobit (trust = educate income age male www) (www = educate income age male)
. global rho=e(rho) // correlation coefficient of disturbances
. global n1 = 6 // the number of parameters in equation 1
. global n2 = 5 // the number of parameters in equation 2

. tabstat educate income age male www, stat(mean) col(variable) save

-----+-----
stats | educate income age male www
-----+-----
mean | 14.24276 24.64864 41.3075 .4505963 .7853492
-----+-----

. matrix ref1 = r(StatTotal),I(1) // reference points for equation 1
. matrix ref1[1,1]=16 // education (college graduation)
. matrix ref1[1,4]=0 // female
. matrix ref1[1,5]=1 // WWW use

. matrix ref2 = ref1[1,1..$n2] // reference points for equation 2
. matrix ref2[1,$n2]=1

. // get parameter estimates
. matrix b0=e(b)
. matrix b1=b0[1,1..$n1] // parameter estimates for equation 1
. matrix b2=b0[1,$n1+1..$n1+$n2] // parameter estimates for equation 2

. matrix xb1=b1*ref1' // compute xb1 of equation 1
. matrix xb2=b2*ref2' // compute xb2 of equation 2

. global xb1=xb1[1,1] // put xb1 into a global macro for computation
. global xb2=xb2[1,1] // put xb1 into a global macro for computation

. // compute the predicted probability at the reference points
. di binormal($xb1, $xb2, $rho)/normal($xb2)
.47208977

. // compute direct effects
. global g1=normalden($xb1)*normal(($xb2-($rho)*$xb1)/sqrt(1-($rho)^2))
. matrix directE=$g1/normal($xb2)*b1
. matrix directE=directE[1,1..$n2]

. // compute indirect effects
. global g2=normalden($xb2)*normal(($xb1-($rho)*$xb2)/sqrt(1-($rho)^2))
. matrix indirectE=($g2/normal($xb2)- ///
(binormal($xb1,$xb2,$rho)*normalden($xb2))/(normal($xb2)^2))*b2
. matrix indirectE[1,$n2]=0
```

```

. // compute overall effects
. matrix Overall=directE+indirectE

...
(the procedure for computing discrete change is skipped)
...

. matrix list Marginal

Marginal[4,5]
      Education      Income      Age      Male      WWW
Reference      16      24.648637      41.307496      0      1
  Direct      .05190699      .0095366      .00535285      .07106867      -.3032191
  Indirect     -.0124106     -.00154447      .00083628     -.00545353      0
  Overall      .03949639      .00799213      .00618913      .06573803     -.28589388

```

Read the last line for overall marginal effects and discrete changes and compare with the output of the `.mfx` above. The overall impact of education on social trust is the sum of direct (.0519) and indirect effects (-.0124). Family income also has negative indirect effect -.0015, but age has both positive direct and indirect effects (.0054 and .0008, respectively).

The following two commands compute marginal effects of equation 1 and 2 (`pmarg1` and `pmarg2`). The predicted probability of trusting people is .4196 at the reference points, while the predicted probability of using WWW in the second equation is .8632.

```

. mfx, predict(pmarg1) at(mean educate=16 male=0 www=1)

Marginal effects after biprobit
  y = Pr(trust=1) (predict, pmarg1)
  = .41959352
-----
variable |      dy/dx      Std. Err.      z      P>|z|      [      95% C.I.      ]      X
-----+-----
educate |      .0480246      .00759      6.33      0.000      .033147      .062903      16
income  |      .0088233      .00258      3.42      0.001      .00377      .013876      24.6486
age     |      .0049525      .00175      2.82      0.005      .001515      .00839      41.3075
male*  |      .0665716      .02941      2.26      0.024      .008926      .124217      0
www*   |     -.2770971      .20246     -1.37      0.171     -.673911      .119717      1
-----
(*) dy/dx is for discrete change of dummy variable from 0 to 1

. mfx, predict(pmarg2) at(mean educate=16 male=0 www=1)

Marginal effects after biprobit
  y = Pr(www=1) (predict, pmarg2)
  = .86317073
-----
variable |      dy/dx      Std. Err.      z      P>|z|      [      95% C.I.      ]      X
-----+-----
educate |      .0331092      .00319     10.37      0.000      .026852      .039366      16
income  |      .0041204      .00145      2.84      0.005      .001277      .006963      24.6486
age     |     -.002231      .00071     -3.13      0.002     -.003628     -.000834      41.3075
male*  |      .0140228      .01825      0.77      0.442     -.021756      .049801      0
www*   |      0      0      .      .      0      0      1
-----
(*) dy/dx is for discrete change of dummy variable from 0 to 1

```

### 4.3 Bivariate Probit Models in SAS: PROC QLIM

In SAS, PROC QLIM is able to estimate both bivariate probit models. Like Stata, SAS allows specifying two equations in a line if they share the same specification. ENDOGENOUS describes characteristics of dependent variables; in this example, they are discrete variables

whose disturbances are normally distributed. Stata and SAS report the same correlation of disturbances ( $\rho=.2008$ ), parameter estimates, and standard errors.

```
PROC QLIM DATA=masil.gss_cdv;
  MODEL trust www = educate income age male;
  ENDOGENOUS trust www ~ DISCRETE(DIST=NORMAL);
RUN;
```

The QLIM Procedure

Discrete Response Profile of trust

Index	Value	Frequency	Percent
1	0	682	58.09
2	1	492	41.91

Discrete Response Profile of www

Index	Value	Frequency	Percent
1	0	252	21.47
2	1	922	78.53

Model Fit Summary

Number of Endogenous Variables	2
Endogenous Variable	trust www
Number of Observations	1174
Log Likelihood	-1298
Maximum Absolute Gradient	0.0004068
Number of Iterations	55
Optimization Method	Quasi-Newton
AIC	2618
Schwarz Criterion	2673

Algorithm converged.

Parameter Estimates

Parameter	DF	Estimate	Standard Error	t Value	Approx Pr >  t
trust.Intercept	1	-2.926969	0.275060	-10.64	<.0001
trust.educate	1	0.102860	0.015059	6.83	<.0001
trust.income	1	0.020288	0.006812	2.98	0.0029
trust.age	1	0.016127	0.002918	5.53	<.0001
trust.male	1	0.165699	0.076609	2.16	0.0305
www.Intercept	1	-1.317767	0.289789	-4.55	<.0001
www.educate	1	0.147825	0.018010	8.21	<.0001
www.income	1	0.018876	0.006580	2.87	0.0041
www.age	1	-0.010398	0.003195	-3.25	0.0011
www.male	1	0.077624	0.086487	0.90	0.3694
_Rho	1	0.200803	0.054268	3.70	0.0002

Now, let us fit the recursive bivariate probit model. Notice that two equations are provided in two separate MODEL statements. The ENDOGENOUS statement is needed to indicate the probability distribution of disturbances in two equations.

```
PROC QLIM DATA=masil.gss_cdv;
  MODEL trust = educate income age male www;
  MODEL www = educate income age male;
  ENDOGENOUS trust www ~ DISCRETE(DIST=NORMAL);
RUN;
```

#### The QLIM Procedure

##### Discrete Response Profile of trust

Index	Value	Frequency	Percent
1	0	682	58.09
2	1	492	41.91

##### Discrete Response Profile of www

Index	Value	Frequency	Percent
1	0	252	21.47
2	1	922	78.53

#### Model Fit Summary

Number of Endogenous Variables	2
Endogenous Variable	trust www
Number of Observations	1174
Log Likelihood	-1297
Maximum Absolute Gradient	0.00327
Number of Iterations	52
Optimization Method	Quasi-Newton
AIC	2619
Schwarz Criterion	2679

Algorithm converged.

#### Parameter Estimates

Parameter	DF	Estimate	Standard Error	t Value	Approx Pr >  t
trust.Intercept	1	-2.532266	0.494644	-5.12	<.0001
trust.educate	1	0.122857	0.019796	6.21	<.0001
trust.income	1	0.022575	0.006640	3.40	0.0007
trust.age	1	0.012681	0.004389	2.89	0.0039
trust.male	1	0.168258	0.074380	2.26	0.0237
trust.www	1	-0.716498	0.574098	-1.25	0.2120
www.Intercept	1	-1.365669	0.292877	-4.66	<.0001
www.educate	1	0.151091	0.018218	8.29	<.0001

www.income	1	0.018804	0.006530	2.88	0.0040
www.age	1	-0.010182	0.003193	-3.19	0.0014
www.male	1	0.066424	0.086610	0.77	0.4431
_Rho	1	0.585570	0.303930	1.93	0.0540

Stata and PROC QLIM produce the same result except for the correlation of disturbances and parameter estimates of WWW use, which are slightly different (e.g., .5863 versus .5856 in  $\rho$  and -.7178 versus -.7165 for WWW use).

#### 4.4 Bivariate Probit Models in LIMDEP (Bivariateprobit\$)

LIMDEP has the `Bivariateprobit$` command to estimate bivariate probit models. The `Lhs=` subcommand lists the two binary dependent variables, whereas `Rh1=` and `Rh2=` respectively specify independent variables for the two equations.

```
BIVARIATEPROBIT;Lhs=TRUST,WWW;
    Rh1=ONE,EDUCATE,INCOME,AGE,MALE;
    Rh2=ONE,EDUCATE,INCOME,AGE,MALE$
```

Normal exit from iterations. Exit status=0.

```
+-----+
| FIML Estimates of Bivariate Probit Model |
| Maximum Likelihood Estimates           |
| Model estimated: Sep 15, 2009 at 03:16:00PM. |
| Dependent variable                     TRUWWW |
| Weighting variable                     None   |
| Number of observations                  1174   |
| Iterations completed                   17     |
| Log likelihood function                 -1297.820 |
| Number of parameters                   11     |
| Info. Criterion: AIC =                  2.22968 |
|   Finite Sample: AIC =                  2.22987 |
| Info. Criterion: BIC =                  2.27716 |
| Info. Criterion:HQIC =                  2.24758 |
+-----+

+-----+-----+-----+-----+-----+-----+
|Variable| Coefficient | Standard Error |b/St.Er.|P[|Z|>z]| Mean of X|
+-----+-----+-----+-----+-----+-----+
-----+Index      equation for TRUST
Constant|  -2.92696771 | .27487860 | -10.648 | .0000 |
EDUCATE|   .10285982 | .01414096 |   7.274 | .0000 | 14.2427598
INCOME |   .02028760 | .00707111 |   2.869 | .0041 | 24.6486371
AGE    |   .01612671 | .00293070 |   5.503 | .0000 | 41.3074957
MALE   |   .16569900 | .07696720 |   2.153 | .0313 | .45059625
-----+Index      equation for WWW
Constant|  -1.31776621 | .29250724 |  -4.505 | .0000 |
EDUCATE|   .14782515 | .01763456 |   8.383 | .0000 | 14.2427598
INCOME |   .01887630 | .00643465 |   2.934 | .0034 | 24.6486371
AGE    |  -.01039833 | .00328982 |  -3.161 | .0016 | 41.3074957
MALE   |   .07762348 | .08744329 |   .888 | .3747 | .45059625
-----+Disturbance correlation
RHO(1,2)|   .20080326 | .05431808 |   3.697 | .0002 |

+-----+
| Joint Frequency Table for Bivariate Probit Model |
| Predicted cell is the one with highest probability |
+-----+
|                                     WWW |
+-----+-----+-----+-----+
| TRUST | 0 | 1 | Total |
+-----+-----+-----+-----+
| 0 | 180 | 502 | 682 |
| Fitted | ( 36) | ( 730) | ( 766) |
+-----+-----+-----+-----+
```

	1	72	420	492
Fitted	(	0)	(	408)
Total	252	922	1174	
Fitted	(	36)	(	1138)

Bivariate Probit Predictions for TRUST and WWW					
Predicted cell (i,j) is cell with largest probability					
Neither TRUST nor WWW predicted correctly					
82 of 1174 observations					
Only	TRUST	correctly predicted			
	TRUST	= 0:	143 of	682	observations
	TRUST	= 1:	25 of	492	observations
Only	WWW	correctly predicted			
	WWW	= 0:	4 of	252	observations
	WWW	= 1:	25 of	922	observations
Both	TRUST	and WWW	correctly predicted		
	TRUST	= 0 WWW	= 0:	15 of	180
	TRUST	= 1 WWW	= 0:	0 of	72
	TRUST	= 0 WWW	= 1:	359 of	502
	TRUST	= 1 WWW	= 1:	218 of	420

The above output suggests that Stata, SAS, and LIMDEP produce same correlation coefficient of errors, parameter estimates, and standard errors with some rounding errors. AIC and BIC are  $2617=2.2297*1,174$  and  $2,673=2.2772*1,174$ , respectively.

Now, fit the recursive bivariate probit model by adding WWW use to the first equation as an endogenous variable. Marginal Effect (or Margin) in the following command computes marginal effects and discrete changes at the means of the independent variables.

```
BIVARIATEPROBIT;Lhs=TRUST,WWW;
  Rh1=ONE,EDUCATE,INCOME,AGE,MALE,WWW;
  Rh2=ONE,EDUCATE,INCOME,AGE,MALE;
  Marginal Effect$
Normal exit from iterations. Exit status=0.
```

```
-----+-----+-----+-----+-----+
| FIML Estimates of Bivariate Probit Model
| Maximum Likelihood Estimates
| Model estimated: Sep 15, 2009 at 00:21:09PM.
| Dependent variable          TRUWWW
| Weighting variable          None
| Number of observations      1174
| Iterations completed        24
| Log likelihood function     -1297.301
| Number of parameters        12
| Info. Criterion: AIC =      2.23050
|   Finite Sample: AIC =      2.23072
| Info. Criterion: BIC =      2.28230
| Info. Criterion:HQIC =      2.25003
|-----+-----+-----+-----+
|Variable| Coefficient | Standard Error |b/St.Er.|P[|Z|>z]| Mean of X|
|-----+-----+-----+-----+-----+
|-----+Index      equation for TRUST
Constant| -2.53127459 | .62810574      | -4.030  |.0001
EDUCATE | .12288180   | .02325478      |  5.284  |.0000  |14.2427598
INCOME  | .02257666   | .00691464      |  3.265  |.0011  |24.6486371
AGE     | .01267296   | .00549849      |  2.305  |.0212  |41.3074957
MALE    | .16824823   | .07532931      |  2.234  |.0255  |.45059625
WWW     | -.71772906  | .79960562      |  -.898  |.3694  |.78534923
|-----+Index      equation for WWW
```

Constant	-1.36574036	.29541029	-4.623	.0000	
EDUCATE	.15109435	.01790608	8.438	.0000	14.2427598
INCOME	.01880339	.00644213	2.919	.0035	24.6486371
AGE	-.01018150	.00326806	-3.115	.0018	41.3074957
MALE	.06639735	.08750730	.759	.4480	.45059625
-----+Disturbance correlation					
RHO(1,2)	.58621974	.42476829	1.380	.1676	

```

+-----+
| Marginal Effects for E[y1|y2=1] |
+-----+-----+-----+-----+
| Variable | Efct x1 | Efct x2 | Efct h1 | Efct h2 |
+-----+-----+-----+-----+
| ONE      | .00000  | .00000  | .00000  | .00000  |
| EDUCATE  | .05291  | -.01572 | .00000  | .00000  |
| INCOME   | .00972  | -.00196 | .00000  | .00000  |
| AGE      | .00546  | .00106  | .00000  | .00000  |
| MALE     | .07245  | -.00691 | .00000  | .00000  |
| WWW     | -.30905 | .00000  | .00000  | .00000  |
+-----+-----+-----+-----+
    
```

```

+-----+
| Partial derivatives of E[y1|y2=1] with |
| respect to the vector of characteristics. |
| They are computed at the means of the Xs. |
| Effect shown is total of 4 parts above. |
| Estimate of E[y1|y2=1] = .499957 |
| Observations used for means are All Obs. |
| Total effects reported = direct+indirect. |
+-----+
    
```

Variable	Coefficient	Standard Error	b/St.Er.	P[ Z >z]	Mean of X
Constant	.000000	.....(Fixed Parameter).....			
EDUCATE	.03718914	.00584175	6.366	.0000	14.2427598
INCOME	.00776473	.00279401	2.779	.0055	24.6486371
AGE	.00651654	.00123352	5.283	.0000	41.3074957
MALE	.06553806	.03045594	2.152	.0314	.45059625
WWW	-.30905460	.38237776	-.808	.4190	.78534923

```

+-----+
| Partial derivatives of E[y1|y2=1] with |
| respect to the vector of characteristics. |
| They are computed at the means of the Xs. |
| Effect shown is total of 4 parts above. |
| Estimate of E[y1|y2=1] = .499957 |
| Observations used for means are All Obs. |
| These are the direct marginal effects. |
+-----+
    
```

Variable	Coefficient	Standard Error	b/St.Er.	P[ Z >z]	Mean of X
Constant	.000000	.....(Fixed Parameter).....			
EDUCATE	.05291298	.01587199	3.334	.0009	14.2427598
INCOME	.00972153	.00344429	2.823	.0048	24.6486371
AGE	.00545698	.00182639	2.988	.0028	41.3074957
MALE	.07244780	.03248863	2.230	.0258	.45059625
WWW	-.30905460	.38237776	-.808	.4190	.78534923

```

+-----+
| Partial derivatives of E[y1|y2=1] with |
| respect to the vector of characteristics. |
| They are computed at the means of the Xs. |
| Effect shown is total of 4 parts above. |
| Estimate of E[y1|y2=1] = .499957 |
| Observations used for means are All Obs. |
| These are the indirect marginal effects. |
+-----+
    
```

Variable	Coefficient	Standard Error	b/St.Er.	P[ Z >z]	Mean of X
Constant	.000000	.....(Fixed Parameter).....			

EDUCATE	-.01572384	.01418159	-1.109	.2675	14.2427598
INCOME	-.00195680	.00186681	-1.048	.2945	24.6486371
AGE	.00105955	.00097193	1.090	.2756	41.3074957
MALE	-.00690973	.01021978	-.676	.4990	.45059625
WWW	.000000	.....(Fixed Parameter).....			

```

+-----+
| Analysis of dummy variables in the model. The effects are |
| computed using E[y1|y2=1,d=1] - E[y1|y2=1,d=0] where d is |
| the variable. Variances use the delta method. The effect |
| accounts for all appearances of the variable in the model. |
+-----+
|Variable      Effect      Standard error      t ratio      |
+-----+
|MALE          .065467      .030353          2.157        |
|WWW           -.296117      .325843         -.909        |
+-----+

```

```

+-----+
| Joint Frequency Table for Bivariate Probit Model |
| Predicted cell is the one with highest probability |
+-----+
|                                     WWW |
+-----+
| TRUST |          0          1          Total |
+-----+
|      0 |      180      |      502      |      682 |
| Fitted | (   54) | (   560) | (   614) |
+-----+
|      1 |       72      |      420      |      492 |
| Fitted | (    0) | (   560) | (   560) |
+-----+
| Total |      252      |      922      |     1174 |
| Fitted | (   54) | (  1120) | (  1174) |
+-----+

```

```

+-----+
| Bivariate Probit Predictions for TRUST and WWW |
| Predicted cell (i,j) is cell with largest probability |
| Neither TRUST nor WWW predicted correctly |
| 166 of 1174 observations |
| Only TRUST correctly predicted |
| TRUST = 0: 25 of 682 observations |
| TRUST = 1: 67 of 492 observations |
| Only WWW correctly predicted |
| WWW = 0: 3 of 252 observations |
| WWW = 1: 67 of 922 observations |
| Both TRUST and WWW correctly predicted |
| TRUST = 0 WWW = 0: 21 of 180 |
| TRUST = 1 WWW = 0: 0 of 72 |
| TRUST = 0 WWW = 1: 356 of 502 |
| TRUST = 1 WWW = 1: 213 of 420 |
+-----+

```

SAS, Stata, and LIMDEP produce almost same parameter estimates and log likelihood, but LIMDEP produces slightly different standard errors. The correlation of disturbances is .5862 in Stata and LIMDEP but is slightly different in SAS ( $\rho=.5856$ ). LIMDEP and Stata report the same conditional predicted probability of 49.9968 percent and conditional marginal effects at the means of covariates. Let us compare the LIMDEP output (direct and indirect effects combined) with the following computed by Stata .mfx.

```

. mfx, predict(pcond1) at(mean male=.450596 www=.785349)

Marginal effects after biprobit
y = Pr(trust=1|www=1) (predict, pcond1)
= .49996773

-----+-----
variable |      dy/dx      Std. Err.      z      P>|z|      [      95% C.I.      ]      X
-----+-----

```

educate		.0371892	.00611	6.09	0.000	.025213	.049165	14.2428
income		.0077648	.00269	2.89	0.004	.002498	.013031	24.6486
age		.0065165	.0012	5.43	0.000	.004164	.008869	41.3075
male*		.0654669	.03028	2.16	0.031	.006124	.12481	.450596
www*		-.2961619	.23328	-1.27	0.204	-.753376	.161052	.785349

(\*) dy/dx is for discrete change of dummy variable from 0 to 1

LIMDEP reports direct and indirect effects separately in addition to direct and indirect effect combined. The first table under the label `Marginal Effects for Ey1|y2=1` right after the parameter estimates summarizes direct and indirect effects. For example, education has a direct effect of .05291 and an indirect effect -.01572, so its overall impact on social trust is the sum of the two effects, which is .0372=.0529-.0157. Stata reports this combined marginal effect. Find the equivalent overall effect in the table under `Total effects reported = direct+indirect` of the above LIMDEP output. LIMDEP produces other two tables for direct (see under `These are the direct marginal effects`) and indirect effects (see under `These are the indirect marginal effects`).

Discrete changes .0655 of male and -.3091 of WWW use under `direct+indirect` in the LIMDEP output are different from those of Stata since LIMDEP computes at the means of all covariates including binary variables; in fact, they are not, by definition, discrete changes (differences in predicted probabilities between `trust=0` and `trust=1`). LIMDEP reports discrete changes ( $E[y_1 | y_2=1, d=1] - E[y_1 | y_2=1, d=0]$ ) separately at the bottom of the output. Find -6.5467 percent for gender and -29.6117 for WWW use.

The following table reports direct, indirect, and overall effects computed manually at the means of covariates in Stata. See the attached Stata script for computation. Notice that the last two numbers (.0655 and -.2962) on row `Overall` are discrete changes of gender and WWW use, respectively.

	Education	Income	Age	Male	WWW
Reference	14.24276	24.648637	41.307496	.45059625	.78534923
Direct	.05291496	.00972179	.0054568	.07244873	-.30910722
Indirect	-.01572574	-.00195703	.00105967	-.00691029	0
Overall	.03718922	.00776475	.00651647	.06546686	-.29616189

Analysis of direct and indirect effects is very useful especially when two effects have opposite signs. For instance, education influences positively social trust in the first equation but has a negative impact (indirect effect) on WWW use in the second equation. Therefore, its overall effect is determined by magnitudes of two effects; the large direct impact dominates in this case, .0372=.0529-.0157. If this specification is correct, a single equation for social trust may mistakenly end up reporting an overestimated impact of education. See Greene (1996, 2003) for discussion about computing and interpreting marginal effects in the recursive bivariate probit model.

Table 4.1 compares the results of bivariate probit models across Stata, SAS, and LIMDEP. In the bivariate probit model, all three software packages report same goodness-of-fit measures, parameter estimates, and the correlation coefficient of disturbance ( $\rho=.2008$ ), but LIMDEP produces slightly different standard errors. In the recursive bivariate probit model, similarly, Stata, SAS, and LIMDEP produce the same parameter estimates and goodness-of-fit measures,

but LIMDEP produce different standard errors. SAS reports a bit different parameter estimate of the endogenous variable (-.7165 versus -.7178) and correlation coefficient ( $\rho=.5856$  versus .5863).

**Table 4.1 Parameter Estimates and Goodness-of-fit of Bivariate Probit Models**

	Bivariate Probit Model			Recursive Bivariate Probit Model		
	Stata	SAS	LIMDEP	Stata	SAS	LIMDEP
Education	.1029 (.0151)	.1029 (.0151)	.1029 (.0141)	.1229 (.0198)	.1229 (.0198)	.1229 (.0233)
Family income	.0203 (.0068)	.0203 (.0068)	.0203 (.0071)	.0226 (.0066)	.0226 (.0066)	.0226 (.0069)
Age	.0161 (.0029)	.0161 (.0029)	.0161 (.0029)	.0127 (.0044)	.0127 (.0044)	.0127 (.0055)
Gender (male)	.1657 (.0766)	.1657 (.0766)	.1657 (.0770)	.1682 (.0744)	.1682 (.0744)	.1682 (.0753)
WWW use				-.7178 (.5729)	-.7165 (.5741)	-.7177 (.7996)
Intercept	-2.9270 (.2751)	-2.9270 (.2751)	-2.9270 (.2749)	-2.5312 (.4939)	-2.5323 (.4946)	-2.5313 (.6281)
Education	.1478 (.0180)	.1478 (.0180)	.1478 (.0176)	.1511 (.0182)	.1511 (.0182)	.1511 (.0179)
Family income	.0189 (.0066)	.0189 (.0066)	.0189 (.0063)	.0188 (.0065)	.0188 (.0065)	.0188 (.0064)
Age	-.0104 (.0032)	-.0104 (.0032)	-.0104 (.0033)	-.0102 (.0032)	-.0102 (.0032)	-.0102 (.0033)
Gender (male)	.0776 (.0865)	.0776 (.0865)	.0776 (.0874)	.0664 (.0866)	.0664 (.0866)	.0664 (.0875)
Intercept	-1.3178 (.2898)	-1.3178 (.2898)	-1.3178 (.2925)	-1.3657 (.2929)	-1.3657 (.2929)	-1.3657 (.2954)
Log likelihood	-1297.8205	-1298	-1297.820	-1297.3007	-1297	1297.301
Likelihood test	185.87			194.40		
Rho ( $\rho$ )	.2008 (.0543)	.2008 (.0543)	.2008 (.0543)	.5863 (.3033)	.5856 (.3039)	.5862 (.4248)
$\chi^2$ to test $\rho=0$	13.1412			2.1296		
AIC	2617.641	2618	2617.644	2618.601	2619	2618.607
BIC (Schwarz)	2673.391	2673	2673.386	2679.419	2679	2679.420

\* AIC\*N and BIC\*N in LIMDEP

## 5. Conclusion

The regression models discussed so far are of categorical dependent variables (binary, ordinal, and nominal responses). An appropriate regression model is determined largely by the measurement level of a categorical dependent variable of interest. The level of measurement should be, however, considered in conjunction with your theory and research questions (Long 1997). You must also examine the data generation process (DGP) of a dependent variable to understand its “behavior.” Experienced researchers pay special attention to censoring, truncation, sample selection, and other particular patterns of the DGP although these limited dependent variable issues are not addressed here.

Generally speaking, if your dependent variable is a binary variable, you may use the binary logit or probit regression model. For ordinal responses, try to fit either ordered logit or probit regression model. If you have a nominal response variable, investigate the DGP carefully and then choose one of the multinomial logit, conditional logit, and nested logit models. In order to use the conditional logit and nested logit, you need to reshape the data set in advance.

You should check key assumptions of a model when fitting the model. Examples are the parallel regression assumption in ordered logit and probit models and the independence of irrelevant alternatives (IIA) assumption in the multinomial logit model. You may respectively conduct the Brant test and Hausman test for these assumptions. If an assumption of an ordered or nominal response model is violated, find alternative models or think carefully if a dependent variable can be explored in a binary response model by dichotomizing the variable.

Since logit and probit models are nonlinear, their parameter estimates are difficult to interpret intuitively. The situation becomes even worse in generalized ordered logit and multinomial logit models, where many parameter estimates and related statistics are produced. Consequently, researchers need to spend more time and effort interpreting the results substantively. Simply reporting parameter estimates and goodness-of-fit statistics is not sufficient. J. Scott Long (1997) and Long and Freese (2003) provide good examples of meaningful interpretations using predicted probabilities, factor changes in odds, and marginal effects (discrete changes) of predicted probabilities. It is highly recommended to visualize marginal effects and discrete changes using a plot of predicted probabilities.

In general, logit and probit models require larger  $N$  than do linear regression models. Like the Bayesian estimation method, the maximum likelihood estimation method depends on data. You need to check if you have sufficient valid observations especially when your data contain many missing values. Scott Long’s rule of thumb says 500 observations and at least additional 10 per independent variable are required in ML estimation. If you have small  $N$ , DO NOT include a large number of independent variables. This is the so called “small  $N$  and large parameter” problem; you may not be able to reach convergence in estimation (you are just torturing SAS or Stata to get nothing) and/or may not get reliable results with desirable asymptotic ML properties. What if 10 parameters are estimated on the basis of 50 observations? By contrast, an extremely large  $N$ , say millions to estimate only two parameters, is not always a virtue since it absurdly boosts the statistical power of a test without adding new information. Even a tiny

effect, which should have been negligible in a normal situation, may be mistakenly reported as statistically significant.

Regarding statistical software packages, I would recommend the SAS LOGISTIC, QLIM, and MDC procedures of SAS/ETS (see Table 2.1 and 3.1). SAS also has PROC GENMOD and PROC PROBIT, but PROC LOGISTIC and PROC QLIM appear to be best for binary and ordinal response models, and PROC MDC is good for nominal dependent variable models. ODS is another advantage of using SAS. I also strongly recommend Stata since it provides handy ways to fit various models and also can be assisted by SPost, which has various useful commands such as `.fitstat`, `.prchange`, `.listcoef`, `.prtab`, and `.prgen`. I encourage SAS Institute to develop additional statements similar to, in particular, `.prchange` and `.prgen`.

LIMDEP supports various regression models for categorical dependent variables addressed in Greene (2003) but does not seem as user-friendly and stable as SAS and Stata. However, LIMDEP computes direct and indirect effects in the recursive bivariate probit model and helps researchers interpret the result in more detail. You may benefit from R's object-oriented programming concept and analyze data flexibly in your own way. SPSS is least recommended mainly due to its limited support for categorical dependent variable models and messy syntax and output.

For logit and probit models for ordinal and nominal outcome variables, see Park, Hun Myoung. 2009. *Regression Models for Ordinal and Nominal Dependent Variables Using SAS, Stata, LIMDEP, and SPSS*. Working Paper. The University Information Technology Services (UITS) Center for Statistical and Mathematical Computing, Indiana University.”  
[http://www.indiana.edu/~statmath/stat/all/cdvm/index\\_nominal.html](http://www.indiana.edu/~statmath/stat/all/cdvm/index_nominal.html)

## Appendix: Data Sets

The sample data set is a subset of the 2000 and 2002 General Social Survey of NORC (<http://www.norc.org>).

[http://www.indiana.edu/~statmath/stat/all/cdvm/gss\\_cdvm.csv](http://www.indiana.edu/~statmath/stat/all/cdvm/gss_cdvm.csv)  
[http://www.indiana.edu/~statmath/stat/all/cdvm/gss\\_cdvm.sas7bdat](http://www.indiana.edu/~statmath/stat/all/cdvm/gss_cdvm.sas7bdat)  
[http://www.indiana.edu/~statmath/stat/all/cdvm/gss\\_cdvm.dta](http://www.indiana.edu/~statmath/stat/all/cdvm/gss_cdvm.dta)

[http://www.indiana.edu/~statmath/stat/all/cdvm/cdvm\\_binary.do](http://www.indiana.edu/~statmath/stat/all/cdvm/cdvm_binary.do) (Stata script)  
[http://www.indiana.edu/~statmath/stat/all/cdvm/cdvm\\_binary.R](http://www.indiana.edu/~statmath/stat/all/cdvm/cdvm_binary.R) (R script)

- `trust`: 1 if a respondent trust most people
- `belief`: Religious intensity: no religion (0) through strong (3)
- `educate`: respondent's education (years)
- `income`: family income (\$1,000.00)
- `age`: respondent's age
- `male`: 1 for male and 0 for female
- `www`: 1 if a respondent have used WWW

```
. sum trust belief educate income age male www, sep(20)
```

Variable	Obs	Mean	Std. Dev.	Min	Max
trust	1174	.4190801	.4936188	0	1
belief	1174	1.892675	1.044809	0	3
educate	1174	14.24276	2.569712	2	20
income	1174	24.64864	6.19427	.5	27.5
age	1174	41.3075	13.40713	18	86
male	1174	.4505963	.4977653	0	1
www	1174	.7853492	.4107548	0	1

```
. tab trust male, miss
```

Social Trust	Gender		Total
	Female	Male	
0	397	285	682
1	248	244	492
Total	645	529	1,174

```
. tab trust www, miss
```

Social Trust	WWW Use		Total
	Non-users	Users	
0	180	502	682
1	72	420	492
Total	252	922	1,174

```
. tab male www, miss
```

Gender	WWW Use		Total
	Non-users	Users	
0	180	502	682
1	72	420	492
Total	252	922	1,174

	Female	Male	Total
Female	149	496	645
Male	103	426	529
Total	252	922	1,174

**. tab belief male, miss**

Religious Intensity	Gender		Total
	Female	Male	
No religion	80	112	192
Somewhat strong	79	55	134
Not very strong	239	217	456
Strong	247	145	392
Total	645	529	1,174

**. tab belief www, miss**

Religious Intensity	WWW Use		Total
	Non-users	Users	
No religion	38	154	192
Somewhat strong	37	97	134
Not very strong	95	361	456
Strong	82	310	392
Total	252	922	1,174

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## Revision History

- 2003. 04 First draft
- 2004. 07 Second draft
- 2005. 09 Third draft (Added bivariate logit/probit and nested logit models)
- 2008. 10 Fourth draft (Added SAS ODS and SPSS output)
- 2009. 09 Fifth draft (Estimated models using different data and rewrote chapter 2-4)