

Maximum-likelihood estimation of the limited-dependent variable model with endogenous explanatory variable

Deon Filmer
The World Bank, US
dfilmer@worldbank.org

Michael Lokshin
The World Bank, US
mlokshin@worldbank.org

Abstract. This article describes the `probitiv` command, which implements the maximum likelihood method to estimate the limited-dependent variable model with endogenous variable.

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1 Introduction

In this article we describe the implementation of the maximum likelihood algorithm to estimate the binary-dependent variable model with an endogenous explanatory variable. The econometric problem of estimating a model with a binary dependent variable with a continuous right hand side variable that may be correlated with the error term arises in a variety of settings:

- Jacoby (1997) estimates a model of take-up of a nutrition supplement program in Jamaica as a function of total household expenditures. Because of measurement error and preference heterogeneity the latter are potentially endogenous. The author estimates a two-stage model using variables that proxy household income or wealth are used as instruments for total expenditures.
- Elbadawi and Sambanis (2002) estimate whether an index of democracy has an effect on whether a country experiences an episode of civil war. The authors are concerned that reverse-causality might affect their results. They estimate a two-stage model with two-period lagged measures of democracy as instruments for the current degree of democracy.
- McGranahan (2000) estimates a model for the determinants of charitable giving in 17th century England. The model for whether or not a gift was given to the poor includes the number of family members mentioned in the will—which is found to increase the probability of charitable giving. The author tests whether this is caused by the “endogeneity” that testators that are simply more philanthropic and are simply more likely to care about the poor as well as others by using instruments derived from the parish in which the testator lived.

These three examples use the approach described in Rivers and Vuong (1988) for estimating a two-stage model that yields consistent estimates.¹ Such an approach requires potentially cumbersome adjustments to derive consistent standard-errors. The `probitiv` command implements Full Information Maximum Likelihood to estimate the binary and continuous parts of the model simultaneously which will yield consistent standard-errors. Like that in Rivers and Vuong (1988) the approach relies of joint normality of the error terms in the binary and continuous equations.

2 Methods

Consider the following two equation simultaneous model (this model is similar to Model 4 in Maddala 1983 p. 120):

$$y_{1i}^* = \gamma y_{2i} + \beta_1 x_{1i} + \varepsilon_{1i} \quad (1.1)$$

$$y_{2i} = \beta_2 x_{2i} + \varepsilon_{2i} \quad (1.2)$$

where

$$y_{1i} = 1 \text{ if } y_{1i}^* > 0$$

$$y_{1i} = 0 \text{ otherwise}$$

and \mathbf{x}_1 and \mathbf{x}_2 are vectors of weakly exogenous variables. The identification conditions in this model are that disturbance terms ε_1 and ε_2 are independent, or else there is at least one variable in \mathbf{x}_1 that is not included in \mathbf{x}_2 . Assume that $(x_1, \varepsilon_1, \varepsilon_2)$ are i.i.d, and ε_1 and ε_2 having, conditional on \mathbf{x}_1 , a joint normal distribution with mean zero and positive definite covariance matrix:

$$\Omega = \begin{bmatrix} 1 & \sigma_{12} \\ \sigma_{21} & \sigma_2^2 \end{bmatrix}$$

Given the assumption with respect to the distribution of the disturbance terms, the logarithmic likelihood function for the system of equation (1.1-1.2) is:

$$\ln L = \sum_i y_{1i} w_i (\ln[F(\eta_i)] + \ln[f(\eta_i)]) + (1 - y_{1i}) w_i (\ln[1 - F(\eta_i)] + \ln[f(\eta_i)]) \quad (2)$$

where F is a cumulative normal distribution function, f is a normal density distribution function, ρ is a correlation between ε_1 and ε_2 , w_i is an optional weight for observation i and

$$\eta_i = \frac{(\beta_1 x_{1i} + \rho(y_{2i} - \beta_2 x_{2i}) / \sigma_2)}{\sqrt{1 - \rho^2}}$$

¹ Smith and Blundell (1988) derive a similar estimation procedure for the Tobit model.

In the maximum likelihood estimation, σ and ρ are not directly estimated. Directly estimated are $\ln \sigma$ and $\operatorname{atanh} \rho$:

$$\operatorname{atanh} \rho = \frac{1}{2} \ln \left(\frac{1 + \rho}{1 - \rho} \right)$$

3 The probitiv command

3.1 Syntax

`probitiv` is implemented as `d2` evaluator that calculates the over log likelihood along with its first and second derivatives. The command allows for weights, robust estimation, as well as the full set of options associated with Stata's maximum likelihood procedures. The generic syntax for the command is:

```
probitiv depvar varlist [weight] [if exp] [in range] ,  
instruments(depvar_s = varlist_s) [robust cluster(varname)  
maximize_options]
```

3.2 Options

`instrument(depvar_s=varlist_s)` gives the specification of the equation for Y_2 . `varlist_s` consists of the exogenous variables in the system and includes the set of instruments that help identify the model. It is an integral part of specifying the `probitiv` model and is not optional.

`robust` specifies that the Huber/White/sandwich estimator of the variance is to be used in place of the conventional MLE variance estimator. `robust` combined with `cluster()` further allows observations which are not independent within cluster (although they must be independent between clusters). If you specify `pweights`, `robust` is implied. See [U] 23.14 Obtaining robust variance estimates.

`cluster(varname)` specifies that the observations are independent across groups (clusters) but not necessarily within groups. `varname` specifies to which group each observation belongs; e.g., `cluster(personid)` in data with repeated observations on individuals. `cluster()` affects the estimated standard errors and variance-covariance matrix of the estimators (VCE), but not the estimated coefficients. `cluster()` can be used with `pweights` to produce estimates for unstratified cluster-sampled data. Specifying `cluster()` implies `robust`.

`maximize_options` control the maximization process; see `maximize`. With the possible exception of `iterate(0)` and `trace`, you should only have to specify them if the model is unstable.

4 Example

We will illustrate the use of the `probitiv` command by the problem of estimating the impact of the distance to the nearest primary school on the probability of school enrollment. A typical specification might be the following:

$$\begin{aligned} (\text{Enrolled})_i = & \alpha + \beta \times (\text{Distance to nearest primary school})_i \\ & + \delta_1 \times (\text{Age Dummy Variables})_i + \delta_2 \times (\text{Male})_i + \varepsilon_i \end{aligned} \quad (1)$$

Where (Enrolled) is observed as a binary variable of whether a child is enrolled in school or not. Other variables in the model might include age and gender of the child.

An objection sometimes raised for such a model is that the distance to the nearest primary school could be “endogenous” because schools might be placed where “they are most needed,” that is, where the underlying probability of enrollment is low. This positive correlation between distance and ε means that schools would typically be located close to children who are less likely to enroll, which would result in an upwardly biased estimate of β .

The “Probit Instrumental Variables” approach simultaneously estimates equation (1) with an equation for the distance to the nearest school. For the sake of illustration, consider the use of a set of dummy variables for region of residence as legitimate instruments for distance to the nearest school.² This would lead to estimating:

$$\begin{aligned} (\text{Distance to nearest primary school})_i = & \gamma_1 \times (\text{Age Dummy Variables})_i + \gamma_2 \times (\text{Male})_i \\ & + \lambda \times (\text{Region Dummy Variables})_i + \mu_i \end{aligned} \quad (2)$$

Applying a standard Probit model in a dataset of 6 to 14 year olds for rural areas in a poor African country yields the following:

```
. probit schin d_prim zage7-zage14 male

Iteration 0:  log likelihood = -2333.6849
Iteration 1:  log likelihood = -1920.839
Iteration 2:  log likelihood = -1912.5393
Iteration 3:  log likelihood = -1912.4923
Iteration 4:  log likelihood = -1912.4923

Probit estimates                               Number of obs   =       3379
                                                LR chi2(10)    =       842.39
                                                Prob > chi2    =       0.0000
Log likelihood = -1912.4923                    Pseudo R2      =       0.1805

-----+-----
      schin |          Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-----+-----
      d_prim |   -0.0573052    .0160758    -3.56  0.000   -0.0888132   -0.0257973
```

² One might argue the validity of this instrument set on the basis that the decision to build schools is made at the regional level, but conditional on the distance to the nearest school the region of residence does not affect enrollment.

zage7	.6036007	.1112158	5.43	0.000	.3856217	.8215796
zage8	.9060991	.1058128	8.56	0.000	.6987097	1.113488
zage9	1.275321	.1091719	11.68	0.000	1.061348	1.489294
zage10	1.638281	.1091079	15.02	0.000	1.424433	1.852128
zage11	1.910501	.1137342	16.80	0.000	1.687586	2.133415
zage12	1.91603	.1096594	17.47	0.000	1.701101	2.130958
zage13	2.071103	.1139791	18.17	0.000	1.847708	2.294497
zage14	1.91747	.1127867	17.00	0.000	1.696412	2.138528
male	-.3014624	.0474146	-6.36	0.000	-.3943933	-.2085315
_cons	-1.075099	.0881272	-12.20	0.000	-1.247825	-.9023729

That is, the coefficient on distance to the nearest primary school is $-.0573$ and is significantly different from zero: in this sample a greater distance to school is associated with lower probability of enrollment. The marginal effect of a change in distance on the probability a child is enrolled in school is: $dF/dX = -0.023$.

Allowing for endogenous school placement and using `probitiv` with region dummy variables as identifying instruments gives the following.

```
. probitiv schin d_prim zage7-zage14 male , instr(d_prim zage7-zage14 male
zregion2-zregion6)
```

```
Iteration 0: log likelihood = -8181.4343
Iteration 1: log likelihood = -8170.5543
Iteration 2: log likelihood = -8170.3271
Iteration 3: log likelihood = -8170.3187
Iteration 4: log likelihood = -8170.3187
```

```
Probit IV                               Number of obs   =       3379
                                         Wald chi2(10)  =       894.20
Log likelihood = -8170.3187             Prob > chi2    =       0.0000
```

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

schin						
d_prim	-.2932207	.0770446	-3.81	0.000	-.4442254 - .142216	
zage7	.5572857	.1109739	5.02	0.000	.3397809 .7747904	
zage8	.855251	.1091819	7.83	0.000	.6412584 1.069244	
zage9	1.165942	.1256413	9.28	0.000	.9196896 1.412194	
zage10	1.523753	.1320002	11.54	0.000	1.265037 1.782468	
zage11	1.761336	.147004	11.98	0.000	1.473213 2.049459	
zage12	1.759638	.1459382	12.06	0.000	1.473604 2.045671	
zage13	1.909265	.152936	12.48	0.000	1.609516 2.209014	
zage14	1.766795	.1468191	12.03	0.000	1.479035 2.054555	
male	-.262274	.0502879	-5.22	0.000	-.3608364 -.1637116	
_cons	-.8699615	.126936	-6.85	0.000	-1.118752 -.6211714	

d_prim						
zage7	.0310029	.1123406	0.28	0.783	-.1891808 .2511865	
zage8	.0631306	.1081325	0.58	0.559	-.1488052 .2750664	
zage9	-.0456569	.1141993	-0.40	0.689	-.2694835 .1781697	
zage10	.0388507	.1122615	0.35	0.729	-.1811779 .2588792	
zage11	-.0142678	.1152455	-0.12	0.901	-.2401449 .2116092	
zage12	-.0656893	.110143	-0.60	0.551	-.2815657 .150187	
zage13	-.037738	.113324	-0.33	0.739	-.2598491 .184373	
zage14	-.0364631	.1140305	-0.32	0.749	-.2599588 .1870327	
male	.0972279	.0534201	1.82	0.069	-.0074736 .2019293	
zregion2	.7926999	.0866229	9.15	0.000	.6229222 .9624776	

zregion3		.0706183	.0814128	0.87	0.386	-.0889478	.2301845
zregion4		-.0192687	.0726982	-0.27	0.791	-.1617546	.1232171
zregion5		.1310172	.1017084	1.29	0.198	-.0683276	.330362
zregion6		.1701614	.0901277	1.89	0.059	-.0064857	.3468085
_cons		.3643652	.0900332	4.05	0.000	.1879034	.540827

/theta		.4013036	.1453618	2.76	0.006	.1163997	.6862075
/lnsig		.4342984	.0121683	35.69	0.000	.4104491	.4581478

rho		.3810638	.1242539			.1158769	.5955401
sigma		1.54388	.0187863			1.507495	1.581143

LR test of indep. eqns. (rho = 0):				chi2(1) =	7.49	Prob > chi2 =	0.0062

The results for Equation (2) are reported in the section of the output with the “d_prim” heading. This is the analogue of the first stage regression in traditional instrumental variables regression.

The results of the model of interest are reported in the section of the output with the “schin” heading. Note that the parameter estimates cannot typically be compared to those of the simple Probit estimates. This is because Probit (and Probit IV) estimates are scaled by the standard error of the error term and this might implicitly differ between the two models. One can, however, compare marginal effects. The marginal effect implied by the `probitiv` estimates is $dF/dX = -.117$, almost a full order of magnitude different than that implied by the `probit` estimates.

The correlation coefficient between the two equations (`rho`) equals .3811. The likelihood ratio test for whether this is significantly different from zero is reported in the last line of the output. In this case the p-value is 0.0062. Since `rho` is positive and significantly different from zero the model suggests that schools are located closer to children who are less likely to be enrolled (i.e. both distance to school and ϵ are small). The significance of this correlation coefficient is a test of the exogeneity of the variable in question (note that the validity of the test rests on the validity of the instruments).

The variables `sigma`, `/theta`, and `/lnsig` are ancillary parameters used in the maximum likelihood procedure. `sigma` is the square-root of the variance of the residuals of the regression part of the model and `lnsig` is its log. `theta` is a transformation of the correlation between the errors from the two equations.

5 References

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