

FIML estimation of an endogenous switching model for count data in Stata 7

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Outline

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- The Model
- **esp** Syntax
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Introduction

- **esp** estimates a FIML endogenous switching Poisson count model (Terza, 1998).
- Cross-section Data.
- Alternative: Two-Stage method of moments (TSM) –not available in Stata.
- `ml d0` method is used –but a `lf` method might be implemented.

THE MODEL

- Conditional on a vector of variables x_i , a dummy d_i , and a random term ε_i , the count y_i has a Poisson distribution

$$f(y_i | \mathbf{e}_i) = \frac{\exp[-\exp(x_i' \mathbf{b} + \mathbf{e}_i)] [\exp(x_i' \mathbf{b} + \mathbf{e}_i)]^{y_i}}{y_i!}$$

- Given a vector of variables z_i , d_i is characterised by

$$d_i = \begin{cases} 1 & \text{if } z_i' \mathbf{a} + v_i > 0 \\ 0 & \text{otherwise.} \end{cases}$$

- Finally, \mathbf{e}_i and v_i are jointly normal with mean zero and covariance matrix

$$\Sigma = \begin{pmatrix} \mathbf{s} & \mathbf{sr} \\ \mathbf{sr} & 1 \end{pmatrix}.$$

- Conditional on ε_i , d_i and y_i are independent. Hence we can write

$$f(y_i, d_i) = \int_{-\infty}^{\infty} \left\{ df(y_i | d_i = 1, \mathbf{e}_i) \Pr(d_i = 1 | \mathbf{e}_i) + (1 - d_i) f(y_i | d_i = 0, \mathbf{e}_i) \Pr(d_i = 0 | \mathbf{e}_i) \right\} f(\mathbf{e}_i) d\mathbf{e}_i$$

- Let w_i be all exogenous variables and consider a change of variable,

$$\mathbf{h}_i = \frac{\mathbf{e}_i}{\mathbf{s} \sqrt{2}}.$$

After some algebra the joint conditional pdf of y_i and d_i becomes

$$f(y_i, d_i | w_i) = \frac{1}{\sqrt{\mathbf{p}}} \int_{-\infty}^{\infty} \left\{ f(y_i | d_i, w_i, \mathbf{s}\mathbf{h}_i \sqrt{2}) \left\{ d_i \Phi^*(\mathbf{s}\mathbf{h}_i \sqrt{2}) + \right. \right. \\ \left. \left. + (1 - d_i) \Phi^*(-\mathbf{s}\mathbf{h}_i \sqrt{2}) \right\} \right\} \exp(-\mathbf{h}_i^2) d\mathbf{h}_i,$$

where,

$$\Phi^*(\mathbf{s}\mathbf{h}\sqrt{2}) = \Phi\left(\frac{z_i' \mathbf{a} + r\mathbf{h}_i \sqrt{2}}{\sqrt{1-r^2}}\right).$$

- Gauss-Hermite quadrature is then used to approximate the integral. Finally, the log-likelihood is simply

$$\text{Log}L = \sum_{i=1}^n \ln\{f(y_i, d_i | w_i)\}.$$

SYNTAX

esp *depvar* [*varlist*] [*if exp*] [*in range*],
e*dum*m*y*(*varname*) [s*witch*(*varlist*)
q*uadrature*(#) r*ho*0(#) s*igma*0(#) m*lopts*]

- *depvar* declares the dependent variable
- *varlist* specifies covariates for the Poisson process
- *edummy* declares endogenous dummy
- *switch* specifies covariates for the switching variable
- *quadrature* indicates the number of quadrature points
- *rho0* sets initial value for ρ -default 0.01-
- *lnsigma0* sets initial value for \mathbf{S} -default 1.0-

EXAMPLE

- Fertility data from the National Survey of Demographic Dynamics 1997 (ENADID), Mexico.
- Dependent variable: Number of children ever born, **children** (includes children who died a few hours or days after birth).
- Endogenous dummy: Completed Primary School, **edu12** (switch variable).

Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
age	19559	45.93481	4.210048	40	54
children	19559	4.428652	2.753055	0	18
catholic	19559	.8943709	.3073702	0	1
indspker	19559	.0940232	.2918685	0	1
after49	19559	.6184365	.4857827	0	1
edu12	19559	.5064676	.4999709	0	1

Comparison model: Poisson count with lognormal heterogeneity

```
. lnhp children catholic indspker after49 edu12, q(16)
```

Getting Initial Values:

Fitting Full model:

Iteration 0: log likelihood = -50093.352

<<omitted output>>

Iteration 8: log likelihood = -44742.419

Poisson Regression--Lognormal Heterogeneity

(16 quadrature points)

Number of obs = 19559

Wald chi2(4) = 4067.23

Prob > chi2 = 0.0000

Log likelihood = -44742.419

children	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
children						
catholic	-.037471	.0129797	-2.89	0.004	-.0629108	-.0120312
indspker	.0259195	.0134347	1.93	0.054	-.000412	.0522509
after49	-.1498286	.0082753	-18.11	0.000	-.1660478	-.1336093
edu12	-.4819543	.0084677	-56.92	0.000	-.4985507	-.4653579
_cons	1.778055	.0137364	129.44	0.000	1.751132	1.804978
sigma	.2965293	.0054761	54.15	0.000	.2859882	.307459

Example: esp

```
. esp children catholic indspker after49 edu12, ed(edu12) s(indspker after49) q(16)
```

Getting Initial Values:

Fitting Full model:

Iteration 0: log likelihood = -63211.383 (not concave)

<<omitted output>>

Iteration 10: log likelihood = -57578.991

Endogenous-Switch Poisson Regression

(16 quadrature points)

Number of obs = 19559

Wald chi2(4) = 2285.21

Prob > chi2 = 0.0000

Log likelihood = -57578.991

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

children						
catholic	-.0355656	.0129769	-2.74	0.006	-.0609999 - .0101313	
indspker	-.2627088	.0187704	-14.00	0.000	-.2994981 - .2259194	
after49	-.0722156	.0099639	-7.25	0.000	-.0917445 - .0526868	
edu12	-1.202968	.0268409	-44.82	0.000	-1.255575 -1.150361	
_cons	2.118148	.0191674	110.51	0.000	2.080581 2.155716	

switch						
indspker	-1.09937	.0384229	-28.61	0.000	-1.174678 -1.024063	
after49	.2901192	.0218779	13.26	0.000	.2472393 .3329992	
_cons	-.076211	.0169429	-4.50	0.000	-.1094186 - .0430035	

sigma	.4632146	.0118455	39.10	0.000	.4405701 .487023	
rho	.9539425	.0102185	93.35	0.000	.929037 .9702418	

Final Comments

- Robust option can be implemented using ml lf method. Speed would also improve.
- FIML estimation of sample selection models for count data might be implemented with relatively minor modifications.
- Zero-inflated models are as well feasible.