

triprobit and the *GHK* simulator: a short note

Antoine Terracol*

1 The trivariate probit

Consider three binary variables y_1 , y_2 and y_3 , the trivariate probit model supposes that:

$$\begin{aligned} y_1 &= \begin{cases} 1 & \text{if } X\beta + \varepsilon_1 > 0 \\ 0 & \text{otherwise} \end{cases} \\ y_2 &= \begin{cases} 1 & \text{if } Z\gamma + \varepsilon_2 > 0 \\ 0 & \text{otherwise} \end{cases} \\ y_3 &= \begin{cases} 1 & \text{if } W\theta + \varepsilon_3 > 0 \\ 0 & \text{otherwise} \end{cases} \end{aligned} \quad (1)$$

with

$$\begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \varepsilon_3 \end{pmatrix} \rightarrow N(0, \Sigma) \quad (2)$$

For identification reasons, the variances of the epsilons must equal 1.

Evaluation of the likelihood function requires the computation of trivariate normal integrals. For example, the probability of observing $(y_1 = 0, y_2 = 0, y_3 = 0)$ is:

$$\Pr [y_1 = 0, y_2 = 0, y_3 = 0] = \int_{-\infty}^{-X\beta} \int_{-\infty}^{-Z\gamma} \int_{-\infty}^{-W\theta} \phi_3(\varepsilon_1, \varepsilon_2, \varepsilon_3, \rho_{12}\rho_{13}\rho_{23}) d\varepsilon_3 d\varepsilon_2 d\varepsilon_1 \quad (3)$$

where $\phi_3(\cdot)$ is the trivariate normal p.d.f., and ρ_{ij} is the correlation coefficient between ε_i and ε_j .

While Stata provides commands to compute univariate and bivariate normal CDF (`norm()` and `binorm()`), no command is available for the trivariate case (as a matter of fact, numerical approximations perform poorly in computing high order integrals).

The `triprobit` command uses the *GHK* (Geweke-Hajivassiliou-Keane) smooth recursive simulator to approximate these integrals

2 The *GHK* simulator

Let us illustrate the *GHK* simulator in the trivariate case (generalization to higher orders is straightforward)

We wish to evaluate

$$\Pr(\varepsilon_1 < b_1, \varepsilon_2 < b_2, \varepsilon_3 < b_3) \quad (4)$$

where $(\varepsilon_1, \varepsilon_2, \varepsilon_3)$ are normal random variables with covariance structure given in (2)

Equation (4) can be rewritten as a product of conditional probabilities:

$$\Pr(\varepsilon_1 < b_1) \Pr(\varepsilon_2 < b_2 | \varepsilon_1 < b_1) \Pr(\varepsilon_3 < b_3 | \varepsilon_1 < b_1, \varepsilon_2 < b_2) \quad (5)$$

Let L be the lower triangular Cholesky decomposition of Σ , such that: $LL' = \Sigma$:

*TEAM, Université de Paris 1 et CNRS, 106-112 boulevard de l'Hôpital, 75647 Paris Cedex 13, France.

Email: terracol@univ-paris1.fr

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$$L = \begin{pmatrix} l_{11} & 0 & 0 \\ l_{21} & l_{22} & 0 \\ l_{31} & l_{32} & l_{33} \end{pmatrix}$$

We get:

$$\begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \varepsilon_3 \end{pmatrix} = \begin{pmatrix} l_{11} & 0 & 0 \\ l_{21} & l_{22} & 0 \\ l_{31} & l_{32} & l_{33} \end{pmatrix} \begin{pmatrix} \nu_1 \\ \nu_2 \\ \nu_3 \end{pmatrix} \quad (6)$$

where the ν_i are *independent* standard normal random variables.

By (6), we get:

$$\begin{aligned} \varepsilon_1 &= l_{11}\nu_1 \\ \varepsilon_2 &= l_{21}\nu_1 + l_{22}\nu_2 \\ \varepsilon_3 &= l_{31}\nu_1 + l_{32}\nu_2 + l_{33}\nu_3 \end{aligned}$$

Thus:

$$\Pr(\varepsilon_1 < b_1) = \Pr(\nu_1 < b_1/l_{11}) \quad (7)$$

and

$$\Pr(\varepsilon_2 < b_2 | \varepsilon_1 < b_1) = \Pr(\nu_2 < (b_2 - l_{21}\nu_1)/l_{22} | \nu_1 < b_1/l_{11}) \quad (8)$$

and

$$\begin{aligned} &\Pr(\varepsilon_3 < b_3 | \varepsilon_1 < b_1, \varepsilon_2 < b_2) = \\ &\Pr(\nu_3 < (b_3 - l_{31}\nu_1 - l_{32}\nu_2)/l_{33} | \nu_1 < b_1/l_{11}, \nu_2 < (b_2 - l_{21}\nu_1)/l_{22}) \end{aligned} \quad (9)$$

Since (ν_1, ν_2, ν_3) are independent random variables, equation (4) can be expressed as a product of univariate CDF, but conditional on unobservables (the ν).

Suppose now that we draw a random variable ν_1^* from a truncated standard normal density with upper truncation point of b_1/l_{11} , and another one, ν_2^* , from a standard normal density with upper truncation point of $(b_2 - l_{21}\nu_1^*)/l_{22}$. These two random variables respect the conditioning events of equations (8) and (9).

Equation (5) is then rewritten as:

$$\Pr(\nu_1 < b_1/l_{11}) \Pr(\nu_2 < (b_2 - l_{21}\nu_1^*)/l_{22}) \Pr(\nu_3 < (b_3 - l_{31}\nu_1^* - l_{32}\nu_2^*)/l_{33}) \quad (10)$$

The *GHK* simulator of (4) is the arithmetic mean of the probabilities given by (10) for D random draws of ν_1^* and ν_2^* :

$$\widetilde{\Pr}_{GHK} = \frac{1}{D} \sum_{d=1}^D \{ \Phi[b_1/l_{11}] \Phi[(b_2 - l_{21}\nu_1^{*d})/l_{22}] \Phi[(b_3 - l_{31}\nu_1^{*d} - l_{32}\nu_2^{*d})/l_{33}] \} \quad (11)$$

where ν_1^{*d} and ν_2^{*d} are the d -th draw of ν_1^* and ν_2^* , and where $\Phi(\cdot)$ is the univariate normal CDF.

The simulated probability (11) is then plugged into the likelihood function, and standard maximisation techniques are used.

3 An example on artificial data

```
set obs 5000
local rho12=0.3
local rho13=-0.3
local rho23=0.3
drawnorm eps1 eps2 eps3 ,corr(1      , 'rho12' , 'rho13' \ /*
                        */ 'rho12' , 1      , 'rho23' \ /*
                        */ 'rho13' , 'rho23' , 1      )
```

```

drawnorm x1 x2 x3 x4 x5 x6 x7 x8 x9
gen y3=(1+x6+x7+x8+x9+eps3>0)
gen y2=(1+x4+x5+x6+eps2>0)
gen y1=(1+y2+y3+x1+x2+x3+eps1>0) /*note that y2 and y3 are endogenous*/
triprobit ( y1= y2 y3 x1 x2 x3)(y2= x4 x5 x6)(y3 = x6 x7 x8 x9)

```

trivariate probit, GHK simulator, 25 draws

Comparison log likelihood = -3876.3152

```

initial:      log likelihood = -3876.3152
<output omitted>
Iteration 5:  log likelihood = -3838.0791

```

```

Log likelihood = -3838.0791
Number of obs   =      5000
Wald chi2(12)  =      3576.34
Prob > chi2    =      0.0000

```

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

y1						
y2	.9232884	.0927705	9.95	0.000	.7414615	1.105115
y3	.9222976	.0765911	12.04	0.000	.7721818	1.072413
x1	1.065994	.0470546	22.65	0.000	.9737688	1.158219
x2	.991229	.0449885	22.03	0.000	.9030532	1.079405
x3	1.037427	.0453475	22.88	0.000	.9485477	1.126307
_cons	1.085532	.0735326	14.76	0.000	.9414105	1.229653

y2						
x4	1.000869	.0338369	29.58	0.000	.9345499	1.067188
x5	.963295	.0340263	28.31	0.000	.8966047	1.029985
x6	1.066905	.0352755	30.24	0.000	.9977661	1.136044
_cons	1.01315	.0314987	32.16	0.000	.9514141	1.074887

y3						
x6	1.023065	.0353343	28.95	0.000	.9538105	1.092319
x7	1.023166	.0351069	29.14	0.000	.9543577	1.091974
x8	1.03172	.0347611	29.68	0.000	.9635901	1.099851
x9	1.017668	.0348807	29.18	0.000	.9493033	1.086033
_cons	1.015376	.0326298	31.12	0.000	.951423	1.079329

athrho12						
_cons	.1457736	.0471507	3.09	0.002	.05336	.2381872

athrho13						
_cons	-.278662	.0546056	-5.10	0.000	-.385687	-.1716371

athrho23						
_cons	.2598698	.0348018	7.47	0.000	.1916596	.32808

```

rho12= .14474975 Std. Err.= .04616273 z= 3.1356413 Pr>|z|= .00171479
rho13= -.27166631 Std. Err.= .05057554 z= -5.3714955 Pr>|z|= 7.809e-08
rho23= .25417374 Std. Err.= .03255343 z= 7.8078952 Pr>|z|= 5.773e-15

```

LR test of rho12=rho13=rho23=0: chi2(3) = 76.472099 Prob > chi2 = 1.752e-16