

Midterm Exam 2 - November 6, 2017

Each sub-question in the following carries equal weight.

1. (24%) Consider the general selection model

$$y_i = \alpha + \beta x_i + u_i,$$

and

$$z_i = \omega + \gamma w_i + v_i,$$

where x_i and w_i are exogenous regressors, the error terms u_i and v_i are mean zero and normally distributed and uncorrelated with regressors and satisfies the standard conditions (no autocorrelation/heteroskedasticity). We normalize the variance of v to unity and assume that u and v are correlated with a correlation coefficient of ρ . We observe y only if $Z = 1$, where $Z = 1$ if $z > 0$ and $Z = 0$, otherwise. We observe Z , whether it is zero or one.

- a) Explain why, if we have 2 generic normally distributed variables X and Y , we can write X as $\gamma Y + u$, where u is independent of Y and γ is a constant. (You have to argue/demonstrate mathematically why u is independent of Y .)
b) If X follows a standard normal distribution, find $E(X|X > a)$.
c) Using the results from a) and b), write down the likelihood function (or log-likelihood) for the general selection model.

2. (30%) Consider the Matlab programs below and fill in the missing part/answering the questions.

3. (16%) Consider the model:

$$y_1 = \alpha_1 x_1 + \alpha_2 x_2 + u_1,$$

Assuming that you have estimated the model by OLS and have the relevant parameter estimates, write down the Wald test for $\alpha_1 = \sqrt{\alpha_2}$.

4. (18%) Consider the simultaneous equation model:

$$(1) \quad y_1 = \alpha_1 y_2 + \alpha_2 x_1 + u_1,$$

and

$$(2) \quad y_2 = \alpha_3 y_1 + \alpha_4 x_1 + \alpha_5 x_2 + u_2.$$

- a) Explain *how* you can use Two-Stage Least Squares (2SLS) to estimate equation (1).
 - b) Explain *why* the 2SLS estimator can consistently estimate the equation for y_1 , but not the one for y_2 .
 - c) Explain in words what the Three-Stage Least Squares estimator does.
4. (12%)
- a) Explain what a duration model is, including a definition of the survivor function and the hazard function.
 - b) Derive the hazard function for the exponential duration model.

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%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%
% Econometrics 2
% Midterm 2
%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%
% Question 1
%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

clear
clc

global w z N

% Set the true parameters and placeholders for results.

N = 500; % Number of observations
beta0 = 0.5; % Intercept for y
beta1 = 3; % Coefficient on X
sigmau = 2; % Standard deviation of u
gamma0 = 1; % Intercept for z0
gamma1 = 4; % Coefficient on W
rho = 0.8; % Correlation between u and v

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%
% Generate the data. The latent variable model for a is:
%
%  $a_0(j) = \beta_0 + \beta_1 x(j) + u(j)$ 
%
% where  $a(j) = a_0(j)$  if  $z_0(j) > 0$  and unobserved otherwise.
%
% The latent variable model for z is:
%
%  $z_0(j) = \gamma_0 + \gamma_1 w(j) + v(j)$ 
%
% where  $z(j) = 1$  if  $z_0(j) > 0$  and 0 otherwise.

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%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
e = mvnrnd([0; 0],[sigmau^2 rho*sigmau; rho*sigmau 1],N);           % Correlated error

u = e(:,1);                                                         % Error terms for a
v = e(:,2);                                                         % Error terms for c

x = ((1:N)'/N).*normrnd(0,1,N,1);
w = ((1:N)'/N).*normrnd(0,1,N,1);

z0 = gamma0*ones(size(w,1),1) + gamma1*w + v;                      % Latent variable z
z = double((z0 > 0));                                              % Observed z.

a0 = beta0*ones(size(x,1),1) + beta1*x + u;                        % Latent variable a

x(z0<=0) = [];                                                     % Gets rid of the z

a = a0;
a(z0<=0) = [];                                                     % Observed a.

% Step 1: Probit.

b0 = [1 1];                                                         % Initial values.

options = optimset('Display','off');                                % Turn off display
[b_mle, ~, ~, ~, ~] = fminunc('logl_prob', b0, options);           % Minimization.

% Step 2: OLS.

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%
%                               FILL IN MISSING CODE
%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

(Write as much as you can, you will get partial points for explaining what needs to be done even
if you forget some of the formulas)

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%
% Question 2
%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
global y x1 x2 T

% Set the true parameters and placeholders for results.

T = 1000; % Sample size.

beta0 = 0.5; % Intercept.
beta1 = 3; % Coefficient on X1
beta2 = 0; % Coefficient on X2

sigma = 1; % Standard deviation

% Generate the data.

x1 = ((1:1:T)'/T).*normrnd(0,1,T,1);
x2 = ones(T,1) + 2.*x1 + 5.*normrnd(0,1,T,1);
x = [ones(T,1) x1 x2];

u = sigma.*randn(T,1);

y = beta0 + beta1.*x1 + beta2.*x2 + u;

% Maximum likelihood estimation.

options = optimset('Display','off');

b0 = [1 1 1 1];
[b1_mle,~,~,~,hess] = fminunc('logl_unres', b0, options); % Unrestricted ML est

b0_res = [1 1 1];
[b2_mle] = fminunc('logl_res', b0_res, options); % Restricted ML est

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%

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% Lagrange Multiplier Test. Null is:
%
%           H0: beta2 = 0
%
% How would loglikelihood function codes and the following code below change
% if instead the null is:
%
%           H0: beta2 = 0 and beta1 = 0
%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

grad_LM = zeros(4,1); % Gradient of unres
grad_LM(1,1) = sum((y - ones(size(y,1),1).*b2_mle(1) - ...
                    b2_mle(2)*x1)/b2_mle(3)^2);
grad_LM(2,1) = sum(x1.*(y - ones(size(y,1),1).*b2_mle(1) - ...
                    b2_mle(2)*x1)./b2_mle(3)^2);
grad_LM(3,1) = sum(x2.*(y - ones(size(y,1),1).*b2_mle(1) - ...
                    b2_mle(2)*x1)/b2_mle(3)^2);
grad_LM(4,1) = sum(ones(size(y,1),1).*(-1/b2_mle(3)) + ...
                    (y - ones(size(y,1),1).*b2_mle(1) - ...
                    b2_mle(2)*x1).^2/b2_mle(3)^3);

vmat_IM = [b2_mle(3)*inv(x'*x) zeros(3,1); % IM estimator eval
           zeros(1,3)    b2_mle(3)/(2*T)];

LM = grad_LM'*vmat_IM*grad_LM; % LM statistic.
pval_LM = chi2cdf(LM,1,'upper'); % p-value.

if pval_LM >= 0.05 % Rejection decision
    reject_LM = 0;
else
    reject_LM = 1;
end

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