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CDSIMEQ: A program to implement two-stage probit least squares

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Abstract. The `cdsimeq` command implements the two-stage probit least squares estimation method described in Maddala (1983) for simultaneous equations models in which one of the endogenous variables is continuous and the other endogenous variable is dichotomous.[1] The `cdsimeq` command implements all the necessary procedures for obtaining consistent estimates for the coefficients, as well as their corrected standard errors.

Keywords: st0038, simultaneous equations, Amemiya, Maddala, continuous endogenous, dichotomous endogenous, 2SPLS, 2SLS, instruments, standard errors

1 Introduction

The problem of simultaneity (or reciprocal causation) and methods of estimating such relationships has been widely discussed in the statistical literature (for general introductions, see Gujarati (1995) and Pindyck and Rubinfeld (1991); for more advanced expositions, see Davidson and MacKinnon (1993), Greene (2000), and Judge et al. (1985)). At issue is the problem that standard estimation methods in the presence of simultaneity will result in biased and inconsistent estimates. This bias can be corrected by choosing one of two popular methods: indirect least squares (ILS) or two-stage least squares (2SLS). The main focus of the literature, however, has been on situations where the endogenous variables are continuous across equations.

In social science research, however, many phenomena of interest can take on only two values or can only be observed as dichotomies. For example, a person either voted or did not vote. This is an example of a phenomenon that naturally has only two possible values. In other cases, such as involvement in militarized interstate disputes, one can argue that the propensity to engage in such disputes is a continuous underlying process, but this propensity can only be observed as a dichotomy; i.e., we can only observe whether a state is/has engaged in a militarized dispute or not. In a single-equation setting, this type of model is easy to fit, and all statistical packages have built-in procedures for estimation; see [R] **probit**, [R] **logit**, and [R] **logistic**.

What if, however, a continuous and a dichotomous variable are hypothesized to simultaneously determine each other? For example, Keshk et al. (2002) are interested

[1] To the best of my knowledge, the term 2SPLS was given to the procedure by Alvarez and Glasgow (2000). Other terms for this procedure include generalized two-stage probit (Amemiya 1978); two-step probit estimator (Guilkey et al. 1992). I prefer 2SPLS because it provides a more complete description of steps and estimations used.

in whether a simultaneous relationship between trade and militarized interstate disputes (MIDs) exists. Trade is a continuous variable whereas MIDs is a dichotomous variable or only observable as a dichotomous variable. In such situations, the options for estimating such relationships using current statistical software packages become extremely limited. This limitation is not due to a lack of statistical literature on how to fit such models, but to the lack of procedures to fit such models in available statistical software packages.[2]

Heckman (1978), Amemiya (1978), and Maddala (1983) all discuss appropriate estimation procedures for such models. Like their continuous counterparts, estimation can proceed through indirect methods (i.e., recovering the structural parameters from reduced form estimates) or through two stage procedures (i.e., creating instruments for the endogenous variables and then substituting them for their endogenous counterparts in the structural equations). In spite of this literature, I am not aware of any statistical package that includes procedures to fit such models. This is puzzling in the age of programmable statistical software programs such as Stata. The command `cdsimeq` is hopefully a first step in filling this void.

2 Background

In order to fully comprehend the usefulness and applicability of the `cdsimeq` command, it is essential to understand the nature of the problem that it is trying to estimate. Equations (1) and (2) present a generic two-equation model,[3]

$$y_1^* = \gamma_1 y_2^* + \boldsymbol{\beta}_1^{'}\mathbf{X}_1 + \varepsilon_1 \tag{1}$$

$$y_2^* = \gamma_2 y_1^* + \boldsymbol{\beta}_2^{'}\mathbf{X}_2 + \varepsilon_2 \tag{2}$$

The proper estimation strategy to be used depends on how y_1^* and y_2^* are observed, as well as whether we are dealing with recursive or nonrecursive models. First, if $y_1 = y_1^*$ and $y_2 = y_2^*$,[4] i.e., both variables are observed, and neither γ_1 nor γ_2 equal zero, then we have the typical simultaneous equations models discussed in the statistical literature. Methods for fitting such models can be found in the previously cited literature. Stata's `reg3` can fit such models; see [R] **reg3**. If theory or prior expectation leads us to believe that $\gamma_1 = 0$ or $\gamma_2 = 0$, but not both, and the error terms are not contemporaneously correlated, then we have a recursive model and each equation can be estimated separately by OLS.[5]

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[2] To the best of my knowledge, no statistical software packages have procedures for fitting this type of model. One Stata program, `probitiv`, written by Jonah Gelbach fits such models; however, it does not correct the standard errors.

[3] The following discussion borrows heavily from Maddala (1983, 242–7).

[4] This corresponds to Maddala's (1983, 243) model 1.

[5] If the error terms are contemporaneously correlated, then estimation can proceed by using seemingly unrelated regressions or other methods; for examples and full discussion, see Greene (2000).

If y_1^* and y_2^* are observed as follows[6]

$$\begin{aligned} y_1 &= y_1^* \\ y_2 &= 1 \text{ if } y_2^* > 0 \\ y_2 &= 0 \text{ otherwise} \end{aligned}$$

and neither γ_1 nor γ_2 equal zero, then we have a model for which `cdsimeq` is written. How to fit such a model is discussed in the next section. If, however, theory or prior expectation leads us to believe that $\gamma_2 = 0$, then we have two interesting situations.

First, if it is hypothesized that y_1^* is only observed given some selection criterion defined by another variable, in this case y_2^*, then we have an example of a sample selection model. While the details of such models are beyond the scope of this paper, the interested readers are directed to Barnow et al. (1981), Breen (1996), and Maddala (1983) for discussion of such models and methods for their estimation. Stata's `treatreg` can perform all the necessary estimations (two-stage and maximum likelihood) for such models; see [R] **treatreg**. On the other hand, if y_1^* is not determined by any selection criterion, $\gamma_1 = 0$ or $\gamma_2 = 0$, but not both, and the error terms are not contemporaneously correlated, then we have a recursive model with a continuous and dichotomous variable and methods for fitting such models are discussed in Maddala and Lee (1976).

A final model of some relevance to our discussion is the following:[7]

$$\begin{aligned} y_1 &= y_1^* \\ y_2 &= y_2^* \text{ if } y_2^* > 0 \\ y_2 &= 0 \text{ otherwise} \end{aligned}$$

If γ_1 and γ_2 are not equal to 0, then we have what Amemiya (1979) calls a simultaneous equation tobit model. Estimation of such models is fully discussed in Amemiya (1979) and Maddala (1983). Readers interested in fitting such a model can cannibalize `cdsimeq` to do so, since the estimation procedures for both models are very similar.[8] While there are several other model possibilities, their discussion is beyond the scope of this paper and interested readers are directed to Maddala (1983).

3 Methods and formulas

The command `cdsimeq` is written to fit a simultaneous equation model in which one of the variables is continuous and the other is dichotomous and as was shown above, this is but one possible model in a class of such models. Adapting current methods for estimating simultaneous equations to a model in which one of the endogenous variables is continuous and the other is dichotomous is straightforward. The only difference is in the appropriate calculation of the standard errors. The discussion that follows will present

[6]This corresponds to Maddala's (1983, 244–5) model 3.
[7]This corresponds to Maddala's (1983, 243–4) model 2.
[8]Interested readers should consult Maddala (1983, 243–4).

the estimation method as it pertains to programming and not to statistical derivation. Readers interested in the statistical derivation aspect are directed to Heckman (1978), Amemiya (1978), and Maddala (1983).

We begin with our simultaneous equations model:

$$y_1 = \gamma_1 y_2^* + \boldsymbol{\beta}_1^{'} \mathbf{X}_1 + \varepsilon_1 \tag{3}$$

$$y_2^* = \gamma_2 y_1 + \boldsymbol{\beta}_2^{'} \mathbf{X}_2 + \varepsilon_2 \tag{4}$$

where
y_1 is a continuous endogenous variable,
y_2^* is a dichotomous endogenous variable, which is observed as a 1 if $y_2^* > 0$, and 0 otherwise,
$\mathbf{X}_1$ and $\mathbf{X}_2$ are matrices of exogenous variables in (3) and (4),
$\beta_1^{'}$ and $\beta_2^{'}$ are vectors of parameters in (3) and (4),
γ_1 and γ_2 are the parameters of the endogenous variables in (3) and (4),
ε_1 and ε_2 are the error terms of (3) and (4).

Because y_2^* is not observed, the structural equations (3) and (4) are rewritten as

$$y_1 = \gamma_1 \sigma_2 y_2^{**} + \beta_1^{'} \mathbf{X}_1 + \varepsilon_1 \tag{5}$$

$$y_2^{**} = \frac{\gamma_2}{\sigma_2} y_1 + \frac{\beta_2^{'}}{\sigma_2} \mathbf{X}_2 + \frac{\varepsilon_2}{\sigma_2} \tag{6}$$

Now estimation follows the typical two-stage estimation process. In the first stage, the following two models are fitted using all of the exogenous variables (i.e., the exogenous variables in both (5) and (6)),

$$y_1 = \mathbf{\Pi}_1^{'} \mathbf{X} + \upsilon_1 \tag{7}$$

$$y_2^{**} = \mathbf{\Pi}_2^{'} \mathbf{X} + \upsilon_2 \tag{8}$$

where
$\mathbf{X}$ is a matrix of all the exogenous variables in (5) and (6),
$\mathbf{\Pi}_1$ and $\mathbf{\Pi}_2$ are vectors of parameters to be estimated,
υ_1 and υ_2 are error terms.

Equation (7) is estimated via OLS and (8) via probit. From these reduced-form estimates, the predicted values from each model are obtained for use in the second stage.

$$\widehat{y}_1 = \widehat{\mathbf{\Pi}}_1 \mathbf{X} \tag{9}$$

$$\widehat{y}_2^{**} = \widehat{\mathbf{\Pi}}_2 \mathbf{X} \tag{10}$$

In the second stage, the original endogenous variables in (5) and (6) are replaced by their respective fitted values in (9) and (10). Thus, in the second stage, the following two models are fitted:

$$y_1 = \gamma_1 \widehat{y}_2^{**} + \boldsymbol{\beta}_1 \mathbf{X}_1 + \varepsilon_1 \tag{11}$$

$$y_2^{**} = \gamma_2 \widehat{y}_1 + \boldsymbol{\beta}_2 \mathbf{X}_2 + \varepsilon_2 \tag{12}$$

Again, (11) is estimated via OLS and (12) is estimated via probit.

The final step in the procedure is the correction of the standard errors. This is necessary because, as can be seen from (11) and (12), the outputted standard errors for each model in the second stage will be based on $\widehat{y}_2^{**}$ and $\widehat{y}_1$ and not on the appropriate y_2^{**} and y_1. Thus, the estimated standard errors in (11) and (12) will be incorrect. The correction that needs to be implemented on the variance–covariance matrices α_1 and α_2, which are the variance–covariance matrices of (11) and (12), respectively, is as follows: First define the following:[9]

$$\alpha_1^{'} = (\gamma_1 \sigma_2, \beta_1^{'})$$

$$\alpha_2^{'} = (\frac{\gamma_2}{\sigma_2}, \frac{\beta_2^{'}}{\sigma_2})$$

$$c = \sigma_1^2 - 2\gamma_1 \sigma_{12}$$

$$d = \left(\frac{\gamma_2}{\sigma_2}\right) \sigma_1^2 - 2\left(\frac{\gamma_2}{\sigma_2}\right)\left(\frac{\sigma_{12}}{\sigma_2}\right)$$

$$H = (\Pi_2, J_1) \tag{13}$$

$$G = (\Pi_1, J_2) \tag{14}$$

$$V_0 = \mathrm{Var}(\widehat{\Pi}_2) \tag{15}$$

With these definitions at hand, and noting that in probit models σ_2 is normalized to 1, the corrected variances of α_1 and α_2 can be obtained as follows:

$$V(\widehat{\alpha_1}) = c(H^{'}X^{'}XH)^{-1} + (\gamma_1\sigma_2)^2(H^{'}X^{'}XH)^{-1}H^{'}X^{'}V_0X^{'}XH(H^{'}X^{'}XH)^{-1} \tag{16}$$

$$V(\widehat{\alpha_2}) = (G^{'}V_0^{-1}G)^{-1} + d(G^{'}V_0^{-1}G)^{-1}G^{'}V_0^{-1}(X^{'}X)^{-1}V_0^{-1}G(G^{'}V_0^{-1}G)^{-1} \tag{17}$$

Everything defined above is easily obtainable from built-in Stata procedures, while others can be obtained by programming Stata. The following are easily obtained via built-in Stata procedures:

[9] What follows is from Maddala (1983, 244–5).

1. The predicted values in (9) and (10) are easily obtained in Stata after running the appropriate statistical procedures.
2. σ_1^2 is the variance of the residuals from (7) and is easily available in Stata after estimating (7).
3. Π_1 in (13) and Π_2 in (14) are the coefficient matrices from (9) and (10) and are available from within Stata, after each estimation.
4. V_0 in (15) is easily obtained from within Stata, after running the probit estimation in (10).

All other values are obtainable through a little programming. For example,

1. $\mathbf{J}_1$ and $\mathbf{J}_2$ are matrices with ones and zeros such that $\mathbf{XJ}_1 = \mathbf{X}_1$ and $\mathbf{XJ}_2 = \mathbf{X}_2$. To create these matrices, a loop procedure is used. Thus, in the creation of $\mathbf{J}_1$, the loop checks the location of exogenous variables in $\mathbf{X}$ against the location of exogenous variables in $\mathbf{X}_1$. The loop then places a one in the row of $\mathbf{J}_1$ for the column location of the exogenous variable, say x_1, in $\mathbf{X}$ and simultaneously a one in the column of $\mathbf{J}_1$ for the column location of x_1 in $\mathbf{X}_1$. A similar loop is used for the creation of the $\mathbf{J}_2$ matrix.
2. Programming is also needed to obtain σ_{12}. It is obtained using the formula $1/N\{\Sigma(d_t\widehat{v}_1)/\widehat{f}\}$ (Amemiya 1978, 1200), where
   a. N is the number of observations.
   b. d_t is the dichotomous endogenous variable.
   c. $\widehat{v}_1$ is the residuals from (7).
   d. $\widehat{f}$ is (10) evaluated using the standard normal density.
3. Finally, the corrections outlined in (16) and (17) are easily obtained using matrix routines within Stata, and the resulting output is easily generated using Stata's estimates post and repost features, see [P] **estimates**.

4 Syntax

`cdsimeq` (*continuous_endogenous_depvar continuous_model_exogenous_indvar(s)*)
(*dichotomous_endogenous_depvar dichotomous_model_exogenous_indvar(s)*)
[`if` *exp*] [`in` *range*] [, `nofirst` `nosecond` `asis` `instpre` `estimates_hold`]

4.1 Options

`nofirst` specifies that the displayed output from the *first stage* estimations be suppressed.

`nosecond` specifies that the displayed output from the *second stage* estimations be suppressed.

`asis` is Stata's `asis` option; see [R] **probit**.

`instpre` specifies that the created instruments in the first stage are not to be discarded after the program terminates. Note that if this option is specified and the program is rerun, an error will be issued saying that the variables already exist. Therefore, these variables have to be dropped or renamed before `cdsimeq` can be rerun.

`estimates_hold` retains the estimation results from the OLS estimation, with corrected standard errors, in a variable called `model_1` and estimation results from the probit estimation, with corrected standard errors, in a variable called `model_2`.[10] Note that if this option is specified the above variables must be dropped before `cdsimeq` command is rerun again with the `estimates_hold` option.

4.2 Stata output

Here is a stylized example for `cdsimeq`:

```
. cdsimeq (continuous  exog3 exog2  exog1 exog4) ( dichotomous exog1 exog2 exog5
> exog6 exog7)

                         NOW THE FIRST STAGE REGRESSIONS
      Source |       SS       df       MS              Number of obs =    1000
-------------+------------------------------           F(  7,   992) =  209.51
       Model |  617.390728     7  88.1986754           Prob > F      =  0.0000
    Residual |  417.608638   992  .420976449           R-squared     =  0.5965
-------------+------------------------------           Adj R-squared =  0.5937
       Total |  1034.99937   999   1.0360354           Root MSE      =  .64883

------------------------------------------------------------------------------
  continuous |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       exog3 |   .1584685   .0218622     7.25   0.000     .1155671    .2013699
       exog2 |   -.009669   .0216656    -0.45   0.655    -.0521846    .0328466
       exog1 |   .1599552   .0212605     7.52   0.000     .1182345    .2016759
       exog4 |   .3165751   .0224563    14.10   0.000     .2725079    .3606424
       exog5 |   .4972074    .021356    23.28   0.000     .4552993    .5391156
       exog6 |  -.0780172   .0217546    -3.59   0.000    -.1207076   -.0353268
       exog7 |   .1611768    .022103     7.29   0.000     .1178028    .2045508
       _cons |   .0107516   .0206197     0.52   0.602    -.0297117     .051215
------------------------------------------------------------------------------

Iteration 0:   log likelihood = -692.49904
Iteration 1:   log likelihood = -424.29883
Iteration 2:   log likelihood = -382.05354
Iteration 3:   log likelihood = -377.16723
Iteration 4:   log likelihood = -377.07132
Iteration 5:   log likelihood = -377.07127
```

(*Continued on next page*)

[10]When this option is specified the created instruments are also preserved.

```
Probit estimates                                  Number of obs   =       1000
                                                  LR chi2(7)      =     630.86
                                                  Prob > chi2     =     0.0000
Log likelihood = -377.07127                       Pseudo R2       =     0.4555

------------------------------------------------------------------------------
dichotomous |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
------------+-----------------------------------------------------------------
      exog3 |   .2134477   .0562479     3.79   0.000     .1032039    .3236916
      exog2 |   .2113067   .0537592     3.93   0.000     .1059406    .3166728
      exog1 |   .4559128    .060367     7.55   0.000     .3375958    .5742299
      exog4 |   .3903133   .0620052     6.29   0.000     .2687852    .5118413
      exog5 |   .7595488   .0646746    11.74   0.000     .6327889    .8863088
      exog6 |   .8546139   .0689585    12.39   0.000     .7194577      .98977
      exog7 |  -.1669142   .0566927    -2.94   0.003    -.2780298   -.0557986
      _cons |   .0835167   .0528104     1.58   0.114    -.0199899    .1870232
------------------------------------------------------------------------------

              NOW THE SECOND STAGE REGRESSIONS WITH INSTRUMENTS

     Source |       SS       df       MS              Number of obs =    1000
------------+------------------------------           F(  5,   994) =  141.20
      Model |  429.827896     5  85.9655791           Prob > F      =  0.0000
   Residual |   605.17147   994  .608824416           R-squared     =  0.4153
------------+------------------------------           Adj R-squared =  0.4124
      Total |  1034.99937   999   1.0360354           Root MSE      =  .78027

------------------------------------------------------------------------------
 continuous |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
------------+-----------------------------------------------------------------
I_dichotom~s |   .2575918   .0214505    12.01   0.000     .2154983    .2996854
      exog3 |   .0425202    .026735     1.59   0.112    -.0099435    .0949838
      exog2 |   .0118544   .0267226     0.44   0.657    -.0405848    .0642937
      exog1 |   .0077736   .0282168     0.28   0.783    -.0475978     .063145
      exog4 |   .3186363   .0283114    11.25   0.000     .2630793    .3741933
      _cons |   .0121851   .0248091     0.49   0.623    -.0364991    .0608692
------------------------------------------------------------------------------

Iteration 0:   log likelihood = -692.49904
Iteration 1:   log likelihood = -424.31527
Iteration 2:   log likelihood =  -382.0779
Iteration 3:   log likelihood = -377.20169
Iteration 4:   log likelihood = -377.10665
Iteration 5:   log likelihood = -377.10661
Probit estimates                                  Number of obs   =       1000
                                                  LR chi2(6)      =     630.78
                                                  Prob > chi2     =     0.0000
Log likelihood = -377.10661                       Pseudo R2       =     0.4554

------------------------------------------------------------------------------
dichotomous |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
------------+-----------------------------------------------------------------
I_continuous |   1.262866   .1604171     7.87   0.000     .9484539    1.577277
      exog1 |   .2509257   .0649992     3.86   0.000     .1235297    .3783218
      exog2 |   .2260372   .0529623     4.27   0.000     .1222331    .3298413
      exog5 |   .1291197   .0958474     1.35   0.178    -.0587377    .3169771
      exog6 |   .9560943   .0721625    13.25   0.000     .8146584     1.09753
      exog7 |  -.3712822   .0674939    -5.50   0.000    -.5035678   -.2389966
      _cons |   .0707977   .0528105     1.34   0.180    -.0327091    .1743044
------------------------------------------------------------------------------
```

NOW THE SECOND STAGE REGRESSIONS WITH CORRECTED STANDARD ERRORS

continuous	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
I_dichotom~s	.2575918	.1043332	2.47	0.014	.0528532	.4623305
exog3	.0425202	.1291476	0.33	0.742	-.210913	.2959533
exog2	.0118544	.1290542	0.09	0.927	-.2413956	.2651044
exog1	.0077736	.1363699	0.06	0.955	-.2598323	.2753795
exog4	.3186363	.1367953	2.33	0.020	.0501956	.587077
_cons	.0121851	.1198708	0.10	0.919	-.2230438	.2474139

dichotomous	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
I_continuous	1.262866	.7397385	1.71	0.088	-.1869952	2.712726
exog1	.2509257	.3130259	0.80	0.423	-.3625938	.8644452
exog2	.2260372	.2737467	0.83	0.409	-.3104964	.7625708
exog5	.1291197	.4827168	0.27	0.789	-.8169878	1.075227
exog6	.9560943	.2825678	3.38	0.001	.4022716	1.509917
exog7	-.3712822	.3265683	-1.14	0.256	-1.011344	.2687799
_cons	.0707977	.2666057	0.27	0.791	-.4517399	.5933353

4.3 Saved results

The command `cdsimeq` provides certain saved results depending on whether the option `estimates_hold` was specified. Without the `estimates_hold` option, the following saved results are provided:

Scalars

`e(sigma_11)`	σ_{11}	`e(sigma_12)`	σ_{12}
`e(gamma_2)`	γ_2	`e(gamma_2_sq)`	γ_2^2
`e(MA_c)`	$\sigma_1^2 - 2\gamma_1\sigma_{12}$	`e(MA_d)`	$(\gamma_2/\sigma_2)\sigma_1^2 - 2\gamma_2\sigma_{12}/\sigma_2^2$
`e(F)`	F from 1st stage	`e(R)`	OLS R from 1st stage
`e(adj_R)`	adjusted R from 1st stage	`e(chi2)`	Probit χ^2 from 1st stage
`e(r2_p)`	Probit Pseudo R from 1st stage		

If `estimates_hold` is specified, then the above results are also returned along with typical estimation results returned by Stata after estimation. See [P] **estimates**.

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