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Calculating Murphy–Topel variance estimates in Stata: A simplified procedure

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Abstract. Building on the work by Hardin (*Stata Journal* 2: 253–266), this note shows how the calculation of the Murphy–Topel variance estimator for two-step models can be simplified in Stata by using the `scores` option of `predict`.

Keywords: st0114, two-step estimation, Murphy–Topel estimator

1 Introduction

In a previous issue of the *Stata Journal*, Hardin (2002) describes the relationship between the sandwich variance estimator for two-step models and the variance estimator suggested by Murphy and Topel (1985). He also illustrates how both variance estimators can be calculated in Stata. This note shows that the calculation procedure suggested by Hardin can be simplified by using Stata's `scores` option of `predict`. An added benefit is that this new approach simplifies changes to the model specification.

2 The Murphy–Topel estimator

Model systems in which one model is embedded in another appear often in the applied literature. A common case is where the prediction from one model is used as a regressor in a second model,

$$\text{Model 1:} \qquad E[y_1 \,|\, \mathbf{X}_1, \theta_1]$$

$$\text{Model 2:} \qquad E[y_2 \,|\, \mathbf{X}_2, \theta_2]$$

where $\mathbf{X}_1(n \times q)$ and $\mathbf{X}_2(n \times p)$ are data matrices and one of the columns in $\mathbf{X}_2$ contains the predicted values from model 1. θ_1 and θ_2 are vectors of parameters that contain the regression coefficients β_1 and β_2, as well as any auxiliary parameters in the models.[1] Since the predicted values from model 1 are included in $\mathbf{X}_2$, the first parameter vector

1. We restrict our attention to two-step models in which each model has one index function/regression equation.

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θ_1 appears in both models, whereas the second parameter vector θ_2 appears only in the second model. Although θ_1 and θ_2 could be estimated jointly, fitting the models by using a two-step procedure is often easier (see Greene 2003, 508, for a discussion). With this approach, model 1 is fitted first, since it does not involve the second parameter vector. Then model 2 is fitted conditional on the results from the first step. Although this approach leads to a consistent estimate of θ_2, the estimated covariance matrix for model 2 needs to be adjusted to take into account the variability in $\widehat{\theta}_1$ (since $\widehat{\theta}_1$ is an estimate of θ_1 rather than its true value).[2]

From Hardin (2002) and Greene (2003), the Murphy–Topel estimate of variance for a two-step model is given by

$$\widehat{\mathbf{V}}_2 + \widehat{\mathbf{V}}_2(\widehat{\mathbf{C}}\widehat{\mathbf{V}}_1\widehat{\mathbf{C}}' - \widehat{\mathbf{R}}\widehat{\mathbf{V}}_1\widehat{\mathbf{C}}' - \widehat{\mathbf{C}}\widehat{\mathbf{V}}_1\widehat{\mathbf{R}}')\widehat{\mathbf{V}}_2$$

where $\widehat{\mathbf{V}}_1(q \times q)$ and $\widehat{\mathbf{V}}_2(p \times p)$ are the estimated covariance matrices for model 1 and model 2, respectively, where each is the model-based estimate not taking into account that the estimate of the parameter vector in model 1 is embedded in model 2.

Further,

$$\widehat{\mathbf{C}} = (p \times q) \text{ matrix given by } \left\{ \sum_{i=1}^{n} \left(\frac{\partial \ln f_{i2}}{\partial \widehat{\theta}_2} \right) \left(\frac{\partial \ln f_{i2}}{\partial \widehat{\theta}_1'} \right) \right\}$$

$$\widehat{\mathbf{R}} = (p \times q) \text{ matrix given by } \left\{ \sum_{i=1}^{n} \left(\frac{\partial \ln f_{i2}}{\partial \widehat{\theta}_2} \right) \left(\frac{\partial \ln f_{i1}}{\partial \widehat{\theta}_1'} \right) \right\}$$

where f_{i1} and f_{i2} are observation i's contribution to the likelihood function of models 1 and 2, respectively. These expressions are conveniently generated using Stata's `scores` option of `predict`. I give examples in the next section.

3 Examples

We begin by replicating the example in Hardin (2002), in which the predicted probabilities from a logit model are used as an explanatory variable in a Poisson model. In this case, neither model has any auxiliary parameters, so $\theta_1 = \beta_1$ and $\theta_2 = \beta_2$. The first step is to fit the models, saving the scores from both models, the predicted values from the first-stage model, the naïve variance estimates, and the estimated coefficient in the second model for the covariate that was predicted in the initial model:

```
/* First stage: logit, save score as s1 */
. logit z age income ownrent selfemp
. predict double s1, scores
```

2. Only the covariance matrix for model 2 needs to be adjusted; the estimated covariance matrix for model 1 is correct.

```
. matrix V1 = e(V)                    // First stage variance estimate
. predict double zhat                 // Generated variable for second stage

/* Second stage: poisson, save score as s2 */
. poisson y age income avgexp zhat
. predict double s2, scores
. matrix V2 = e(V)
. scalar zz = _b[zhat]                // Coeff on generated variable
```

The next step is to calculate $\widehat{\mathbf{C}}$ and $\widehat{\mathbf{R}}$, but first we'll need some more notation to identify the pieces on information that go into $\widehat{\mathbf{C}}$ and $\widehat{\mathbf{R}}$. Let $\mathbf{x}_{i1}$ be the ith row of matrix $\mathbf{X}_1$ and $\mathbf{x}_{i2}$ the ith row of matrix $\mathbf{X}_2$. z_i and y_i are the dependent variables in the first- and second-stage models, respectively; $\widehat{z}_i$ and $\widehat{y}_i$ are the model predictions; and $\widehat{\gamma}$ is the estimated coefficient for $\widehat{z}_i$ in model 2. Using the chain rule, we see that the partial derivatives in $\widehat{\mathbf{C}}$ and $\widehat{\mathbf{R}}$ are functions of $\mathbf{x}_{i1}$, $\mathbf{x}_{i2}$, $\widehat{\gamma}$, the equation-level scores from each model, and a partial derivative of $\widehat{z}_i$.

$$
\begin{aligned}
\frac{\partial \ln f_{i1}}{\partial \widehat{\beta}_1} &= \frac{\partial \ln f_{i1}}{\partial (\mathbf{x}_{i1}\widehat{\beta}_1)} \frac{\partial (\mathbf{x}_{i1}\widehat{\beta}_1)}{\partial \widehat{\beta}_1} \\
&= \frac{\partial \ln f_{i1}}{\partial (\mathbf{x}_{i1}\widehat{\beta}_1)} \mathbf{x}_{i1} \\
\frac{\partial \ln f_{i2}}{\partial \widehat{\beta}_2} &= \frac{\partial \ln f_{i2}}{\partial (\mathbf{x}_{i2}\widehat{\beta}_2)} \mathbf{x}_{i2} \\
\frac{\partial \ln f_{i2}}{\partial \widehat{\beta}_1} &= \frac{\partial \ln f_{i2}}{\partial (\mathbf{x}_{i1}\widehat{\beta}_1)} \mathbf{x}_{i1} = \frac{\partial \ln f_{i2}}{\partial (\mathbf{x}_{i2}\widehat{\beta}_2)} \frac{\partial (\mathbf{x}_{i2}\widehat{\beta}_2)}{\partial (\mathbf{x}_{i1}\widehat{\beta}_1)} \mathbf{x}_{i1} \\
&= \frac{\partial \ln f_{i2}}{\partial (\mathbf{x}_{i2}\widehat{\beta}_2)} \frac{\partial \widehat{z}_i}{\partial (\mathbf{x}_{i1}\widehat{\beta}_1)} \ \widehat{\gamma} \ \mathbf{x}_{i1}
\end{aligned}
$$

For the logit model the derivative of $\widehat{z}_i$ with respect to model 1's index function equals $\widehat{z}_i(1-\widehat{z}_i)$ since $\widehat{z}_i = \exp(\mathbf{x}_{i1}\widehat{\beta}_1)/\{1+\exp(\mathbf{x}_{i1}\widehat{\beta}_1)\}$. With these results, we can rewrite $\widehat{\mathbf{C}}$ and $\widehat{\mathbf{R}}$ as follows,

$$
\widehat{\mathbf{C}} = \sum_{i=1}^{n} \mathbf{x}'_{i2} \left\{ s_{i2}^2 \frac{\partial \widehat{z}_i}{\partial (\mathbf{x}_{i1}\widehat{\beta}_1)} \widehat{\gamma} \right\} \mathbf{x}_{i1} = \mathbf{X}'_2 \mathrm{Diag} \left\{ s_{i2}^2 \frac{\partial \widehat{z}_i}{\partial (\mathbf{x}_{i1}\widehat{\beta}_1)} \widehat{\gamma} \right\} \mathbf{X}_1
$$

$$
\widehat{\mathbf{R}} = \sum_{i=1}^{n} \mathbf{x}'_{i2} \left\{ s_{i2} s_{i1} \right\} \mathbf{x}_{i1} = \mathbf{X}'_2 \mathrm{Diag} \left\{ s_{i2} s_{i1} \right\} \mathbf{X}_1
$$

where

$$
s_{i1} = \frac{\partial \ln f_{i1}}{\partial (\mathbf{x}_{i1}\widehat{\beta}_1)} \qquad \text{and} \qquad s_{i2} = \frac{\partial \ln f_{i2}}{\partial (\mathbf{x}_{i2}\widehat{\beta}_2)}
$$

This structure is common for all two-step models in which each model has one index function and no auxiliary parameters (when the models have auxiliary parameters, the

calculations are somewhat more complicated as we will see below). With this information it is straightforward to compute the $\widehat{\mathbf{C}}$ and $\widehat{\mathbf{R}}$ matrices by using Stata's `matrix accum` command as suggested by Hardin:

```
                                    // Calculate C using scores
. matrix accum C = age income ownrent selfemp const age income avgexp zhat
> const [iw=s2*s2*zhat*(1-zhat)*zz], nocons
                                    // Calculate R using scores
. matrix accum R = age income ownrent selfemp const age income avgexp zhat
> const [iw=s2*s1], nocons
                                    // Get only the desired partition
. matrix C = C[6..10,1..5]
. matrix R = R[6..10,1..5]
. matrix M = V2 + (V2 * (C*V1*C' - R*V1*C' - C*V1*R') * V2)
. capture program drop doit
. matrix b = e(b)
. program define doit, eclass
        ereturn post b M
        ereturn local vcetype "Mtopel"
        ereturn display
  end
. doit
```

	Mtopel					
	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
y						
age	.0731059	.1096293	0.67	0.505	-.1417636	.2879755
income	.0452336	.4375397	0.10	0.918	-.8123285	.9027957
avgexp	-.0068969	.004265	-1.62	0.106	-.0152561	.0014623
zhat	4.632355	10.82669	0.43	0.669	-16.58757	25.85228
_cons	-6.319947	9.661564	-0.65	0.513	-25.25626	12.61637

For comparison, the Poisson output with unadjusted standard errors is given below:

```
Poisson regression                              Number of obs   =        100
                                                LR chi2(4)      =      27.21
                                                Prob > chi2     =     0.0000
Log likelihood = -78.330992                     Pseudo R2       =     0.1480
```

y	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
age	.0731059	.0542458	1.35	0.178	-.0332139	.1794258
income	.0452336	.1741114	0.26	0.795	-.2960184	.3864856
avgexp	-.0068969	.00202	-3.41	0.001	-.0108561	-.0029378
zhat	4.632355	3.661774	1.27	0.206	-2.54459	11.8093
_cons	-6.319947	3.930768	-1.61	0.108	-14.02411	1.384217

The manual calculation (that which must be derived and then specified by the user) for calculation of the estimates involves the evaluation of $\partial\widehat{z}_i/\partial(\mathbf{x}_{i1}\widehat{\beta}_1)$; the `scores` option of `predict` makes the remaining calculation in Hardin's procedure redundant.

The main advantage of deriving the Murphy–Topel variance estimate in this way is that modifying the code to use a different model in one of the two steps is easy. If, for example, one were interested in using a probit model in the second step instead of a Poisson model, one need only replace `poisson` with `probit` in the code above. This change produces the following results:

	Mtopel					
	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
age	.040167	.0375665	1.07	0.285	-.0334619	.1137959
income	.1221488	.1441061	0.85	0.397	-.1602941	.4045916
avgexp	-.0023466	.0010854	-2.16	0.031	-.0044739	-.0002192
zhat	2.152821	2.385346	0.90	0.367	-2.522371	6.828014
_cons	-3.8865	2.604024	-1.49	0.136	-8.990293	1.217293

Changing the first-stage model to a probit instead of a logit takes a little more work since we have to take into account that the derivative of $\widehat{z}_i$ with respect to model 1's index function now equals $\phi(\mathbf{x}_{i1}\widehat{\beta}_1)$ since $\widehat{z}_i = \Phi(\mathbf{x}_{i1}\widehat{\beta}_1)$. In addition to changing `logit` to `probit` in the code and saving the linear prediction from the probit model as variable `xb`, we must change the line calculating $\widehat{\mathbf{C}}$ as follows,

```
// Calculate C using scores
. matrix accum C = age income ownrent selfemp const age income avgexp zhat
> const [iw=s2*s2*normalden(xb)*zz], nocons
```

which produces the following results:

	Mtopel					
	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
y						
age	.0803012	.1509582	0.53	0.595	-.2155714	.3761738
income	.0397158	.5221716	0.08	0.939	-.9837218	1.063153
avgexp	-.0068861	.0047102	-1.46	0.144	-.0161178	.0023457
zhat	5.393431	14.91054	0.36	0.718	-23.83068	34.61755
_cons	-7.094363	13.68211	-0.52	0.604	-33.9108	19.72207

To use a linear regression model in the first step takes a little more work since we have to modify the results from the `regress` command to get the maximum likelihood estimates of the covariance matrix and the mean squared error of the regression:

```
. reg z age income ownrent selfemp   // First stage: regression
. predict double zhat                // Generated variable for second stage
. predict double res, res            // Get residuals + squared residuals
. gen double res2 = res^2
. quietly sum res2
. scalar mse = r(mean)               // ML estimate of sigma^2
. matrix V1 = (e(df_r)/e(N))*e(V)    // ML estimate of covariance matrix
. gen double s1 = res*(1/mse)        // Generate score
```

Further, we must amend the code to take into account that the derivative of $\widehat{z}_i$ with respect to model 1's index function now equals 1 since $\widehat{z}_i = \mathbf{x}_{i1}\widehat{\beta}_1$,

```
                                        // Calculate C using scores
. matrix accum C = age income ownrent selfemp const age income avgexp zhat
> const [iw=s2*s2*zz], nocons
```

which produces the following results:

```
. doit
```

	Mtopel Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
y						
age	.1097948	.4069624	0.27	0.787	-.6878369	.9074264
income	-.0550747	1.280603	-0.04	0.966	-2.565009	2.45486
avgexp	-.0068635	.0061429	-1.12	0.264	-.0189034	.0051765
zhat	7.46005	34.49451	0.22	0.829	-60.14795	75.06805
_cons	-9.27511	33.76454	-0.27	0.784	-75.45239	56.90217

If we want to use a negative binomial model instead of a Poisson model in the second stage, we have to take into account the auxiliary (dispersion) parameter in the negative binomial model when deriving the Murphy–Topel variance estimate. Now θ_2 has two segments: the regression coefficients β_2 and the auxiliary parameter α.[3] Here we have the following,

$$\widehat{\mathbf{C}} = \sum_{i=1}^{n} \widetilde{\mathbf{x}}'_{i2} \left\{ s_{i2}^2 \frac{\partial \widehat{z}_i}{\partial(\mathbf{x}_{i1}\widehat{\beta}_1)} \widehat{\gamma} \right\} \mathbf{x}_{i1} = \widetilde{\mathbf{X}}'_2 \mathrm{Diag} \left\{ s_{i2}^2 \frac{\partial \widehat{z}_i}{\partial(\mathbf{x}_{i1}\widehat{\beta}_1)} \widehat{\gamma} \right\} \mathbf{X}_1$$

$$\widehat{\mathbf{R}} = \sum_{i=1}^{n} \widetilde{\mathbf{x}}'_{i2} \left\{ s_{i2} s_{i1} \right\} \mathbf{x}_{i1} = \widetilde{\mathbf{X}}'_2 \mathrm{Diag} \left\{ s_{i2} s_{i1} \right\} \mathbf{X}_1$$

where

$$\widetilde{\mathbf{X}}_2 = \left(\mathbf{X}_2, \frac{a_i}{s_{i2}} \right) \qquad \text{and} \qquad a_i = \frac{\partial \ln f_{i2}}{\partial \alpha}$$

The only correction necessary to allow for the presence of the auxiliary parameter is to replace $\mathbf{X}_2$ with $\widetilde{\mathbf{X}}_2$ in the previous equations. $\widetilde{\mathbf{X}}_2$ is simply $\mathbf{X}_2$ with an additional column appended that contains the derivative of the log-likelihood function with respect to the auxiliary parameter divided by the derivative of the log-likelihood function with respect to the index function.[4] Both these derivatives/scores can be calculated in Stata by specifying the `scores` option with `predict` after running `nbreg`. The code and results are given below:

3. α Is used here generally to denote an auxiliary parameter; it should not be confused with the α in the description of the `nbreg` command in the Stata manual (our α actually equals $\ln \alpha$ in the manual).

4. We divide by s_{i2} to undo the weighting by s_{i2} in the square brackets.

```
. logit z age income ownrent selfemp
. predict double s1, scores
. matrix V1 = e(V)
. predict double zhat
. nbreg y age income avgexp zhat
. predict double s2 a, scores
. matrix V2 = e(V)
. scalar zz = _b[zhat]
. gen a_s = a / s2                    // Divide a by s2 to undo weighting below
                                      // Calculate C using scores
. matrix accum C = age income ownrent selfemp const age income avgexp zhat
> const a_s [iw=s2*s2*zhat*(1-zhat)*zz], nocons
                                      // Calculate R using scores
. matrix accum R = age income ownrent selfemp const age income avgexp zhat
> const a_s [iw=s2*s1], nocons
                                      // Get only the desired partition
. matrix C = C[6..11,1..5]
. matrix R = R[6..11,1..5]
. matrix M = V2 + (V2 * (C*V1*C' - R*V1*C' - C*V1*R') * V2)
. matrix b = e(b)
. doit
```

	Mtopel					
	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
y						
age	.107657	.1097165	0.98	0.326	-.1073833	.3226973
income	.0209116	.3621894	0.06	0.954	-.6889665	.7307897
avgexp	-.005743	.0023503	-2.44	0.015	-.0103495	-.0011365
zhat	6.469631	7.848509	0.82	0.410	-8.913164	21.85243
_cons	-8.807249	8.353285	-1.05	0.292	-25.17939	7.564889
lnalpha						
_cons	1.15111	.5468807	2.10	0.035	.0792434	2.222976

What if there is more than one auxiliary parameter in the model? This situation can easily be accommodated using the above setup. Say that we wanted instead to use an ordered probit in the second stage and a probit in the first stage. Collapsing the dependent variable to three categories—0, 1, and 2, where 2 is "2 or higher"—produces a model with two auxiliary parameters or cutoff points. Here

$$\widetilde{\mathbf{X}}_2 = \left(\mathbf{X}_2, \frac{a_i^1}{s_{i2}}, \frac{a_i^2}{s_{i2}}\right) \quad \text{where} \quad a_i^1 = \frac{\partial \ln f_{i2}}{\partial \alpha^1} \quad \text{and} \quad a_i^2 = \frac{\partial \ln f_{i2}}{\partial \alpha^2}$$

where α^1 and α^2 are the two auxiliary parameters in the model. The following code estimates the models and produces the Murphy–Topel variance estimate:

```
. probit z age income ownrent selfemp
. predict double s1, scores
. matrix V1 = e(V)
```

```
. predict double zhat
. predict xb, xb                    // Generate linear prediction
. gen y_ordered = y                 // Generate depvar for ordered probit
. recode y_ordered (3=2) (4=2) (7=2)
. oprobit y_ordered age income avgexp zhat
. predict double s2 a1 a2, scores
. matrix V2 = e(V)
. scalar zz = _b[zhat]
. gen a1_s = a1 / s2                // Divide by s2 to undo weighting below
. gen a2_s = a2 / s2
                                    // Calculate C using scores
. matrix accum C = age income ownrent selfemp const age income avgexp zhat
> a1_s a2_s [iw=s2*s2*normalden(xb)*zz], nocons
                                    // Calculate R using scores
. matrix accum R = age income ownrent selfemp const age income avgexp zhat
> a1_s a2_s [iw=s2*s1], nocons
                                    // Get only the desired partition
. matrix C = C[6..11,1..5]
. matrix R = R[6..11,1..5]
. matrix M = V2 + (V2 * (C*V1*C' - R*V1*C' - C*V1*R') * V2)
. matrix b = e(b)
. doit
```

	Mtopel					
	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
y_ordered						
age	.0415961	.0383581	1.08	0.278	-.0335844	.1167766
income	.1451392	.1519067	0.96	0.339	-.1525924	.4428708
avgexp	-.0028311	.0011394	-2.48	0.013	-.0050644	-.0005978
zhat	2.551639	2.640499	0.97	0.334	-2.623645	7.726922
cut1						
_cons	4.237672	2.859636	1.48	0.138	-1.367112	9.842456
cut2						
_cons	4.799178	2.871063	1.67	0.095	-.8280026	10.42636

4 Conclusion

This note demonstrates how the Murphy–Topel variance estimator for two-step models can be calculated in Stata by using the `scores` option of `predict`. This approach reduces the amount of calculation needed to obtain the variance estimate and makes changing from one model specification to another straightforward.

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