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example 2c — Linear regression with endogenous treatment

Description Remarks and examples Also see

Description

Continuing from [ERM] **example 2b**, we now consider the case where the treatment is endogenous and the variance and correlation parameters differ by treatment group.

Remarks and examples

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In [ERM] **example 2b**, we assumed that graduating from college was an exogenous treatment. However, unobserved factors such as ability may affect whether individuals graduate from college and also affect their wage. Thus, it may be more appropriate for us to treat having a college degree as an endogenous treatment. We found endogeneity in [ERM] **example 2a**, which analyzes the treatment instead as a binary endogenous covariate. You may want to compare the result of this example with the results from [ERM] **example 2b**.

Because college graduation is now assumed to be endogenous, we must specify a model for `college`. We model graduation as a function of the level of parental education (`peduc`), which we further assume does not have a direct effect on wage. The endogenous treatment equation is specified in option `entreat()`.

```
. eregress wage c.age##c.age tenure, entreat(college = i.peduc) vce(robust)

Iteration 0:   log pseudolikelihood = -17382.446
Iteration 1:   log pseudolikelihood = -17381.922
Iteration 2:   log pseudolikelihood =  -17381.92

Extended linear regression                      Number of obs     =      6,000
                                                Wald chi2(8)      =  348743.60
Log pseudolikelihood =  -17381.92               Prob > chi2       =     0.0000
```

	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
wage						
college# c.age						
no	.2338084	.0176633	13.24	0.000	.199189	.2684279
yes	.6777385	.0219827	30.83	0.000	.6346531	.7208239
college# c.age#c.age						
no	-.0018611	.00019	-9.79	0.000	-.0022335	-.0014887
yes	-.0052533	.0002372	-22.14	0.000	-.0057183	-.0047883
college# c.tenure						
no	.3948863	.0207452	19.04	0.000	.3542263	.4355462
yes	.5883544	.0257213	22.87	0.000	.5379415	.6387673
college						
no	10.86301	.3675208	29.56	0.000	10.14268	11.58333
yes	3.184255	.4612019	6.90	0.000	2.280316	4.088194
college						
peduc						
college	.849575	.0356419	23.84	0.000	.7797181	.9194318
graduate	1.347272	.0491996	27.38	0.000	1.250843	1.443701
doctorate	1.541025	.1174797	13.12	0.000	1.310769	1.771281
_cons	-.973061	.0292791	-33.23	0.000	-1.030447	-.9156749
var(e.wage)	7.629807	.2245651			7.202122	8.082889
corr(e.col~e, e.wage)	.623109	.0267317	23.31	0.000	.5679046	.6727326

As in [ERM] **example 2b**, we can interpret the coefficients in the `wage` equation as coefficients in separate models for the two potential outcomes—the models for those with and without a college degree. The estimated correlation between the errors from the main and auxiliary equations is 0.62. We could use the z statistic for the correlation to test for endogeneity. We could also use the `estat teffects` and `margins` commands to answer questions related to the entire population or specific subpopulations. However, we will not interpret the results of this model any further because we will first extend it.

Above, we assumed that the relationship between the unobserved factors that affect wage and the unobserved factors that affect whether individuals graduate from college was the same for those individuals with a college degree and those without. We do not have a good reason to believe that these will be the same, so we specify the suboption `pocorrelation` within the option `entreat()` to model separate correlation parameters for the two potential outcomes. We also assumed that the unobserved factors affecting wage were equally variable for those who had a college degree and

those who did not. We can relax this assumption and model different variances for the two potential outcomes by specifying the suboption `povariance` within the option `entreat()`.

```
. eregress wage c.age##c.age tenure,
> entreat(college = i.peduc, povariance pocorrelation) vce(robust)
Iteration 0:   log pseudolikelihood = -17382.446
Iteration 1:   log pseudolikelihood = -17381.327
Iteration 2:   log pseudolikelihood = -17381.319
Iteration 3:   log pseudolikelihood = -17381.319
Extended linear regression                      Number of obs     =      6,000
                                                Wald chi2(8)      =  104887.19
Log pseudolikelihood = -17381.319               Prob > chi2       =     0.0000
```

	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
wage						
college# c.age						
no	.234277	.0176793	13.25	0.000	.1996261	.2689278
yes	.6759938	.0220455	30.66	0.000	.6327854	.7192021
college# c.age#c.age						
no	-.0018627	.00019	-9.80	0.000	-.0022351	-.0014902
yes	-.0052427	.0002376	-22.07	0.000	-.0057084	-.0047771
college# c.tenure						
no	.3917974	.0211184	18.55	0.000	.350406	.4331887
yes	.5951107	.0264841	22.47	0.000	.5432027	.6470187
college						
no	10.82487	.3712505	29.16	0.000	10.09723	11.55251
yes	3.097338	.4678998	6.62	0.000	2.180271	4.014405
college						
peduc						
college	.8482632	.0356294	23.81	0.000	.7784309	.9180955
graduate	1.343223	.0493492	27.22	0.000	1.2465	1.439945
doctorate	1.538188	.1162237	13.23	0.000	1.310393	1.765982
_cons	-.9715507	.0292856	-33.18	0.000	-1.028949	-.9141521
var(e.wage)						
college						
no	7.46846	.2657898			6.965275	8.007997
yes	7.98125	.3990003			7.236315	8.802871
corr(e.col~e, e.wage)						
college						
no	.6057846	.0374579	16.17	0.000	.5271994	.6740954
yes	.6518029	.0359868	18.11	0.000	.5755573	.7168138

We see separate variance and correlation parameters for those with a college degree and those without. The estimated correlation between the errors from the main and auxiliary equation is 0.61 for individuals without a college degree and 0.65 for those with a college degree. The z statistics may be used for Wald tests of the null hypothesis that there is no endogenous treatment. For both treatment groups, we reject this hypothesis and conclude that having a college degree is an endogenous

treatment. Because the estimates are positive, we conclude that unobserved factors that increase the chance of having a college degree also tend to increase wage.

We can use `estat teffects` to estimate the average effect of a college degree on wage. We use the `atet` option to estimate the ATET.

```
. estat teffects, atet
Predictive margins                              Number of obs     =      6,000
                                                Subpop. no. obs   =      2,234
```

	Unconditional Margin	Std. Err.	z	P>|z|	[95% Conf.	Interval]
ATET						
college (yes vs no)	5.238589	.1754972	29.85	0.000	4.894621	5.582558

We estimate that the average wage for those who graduated from college is \$5.24 higher than it would have been had those same individuals not graduated from college. This is \$2.39 less than the result from our model in [ERM] **example 2b** that did not account for the endogeneity of college graduation. We said "same individuals" to emphasize that \$5.24 is a treatment effect on those who chose to attend college and graduated. More formally, it is our estimate of what the average increase in wage is in the whole population for everyone who chose to attend college and graduated.

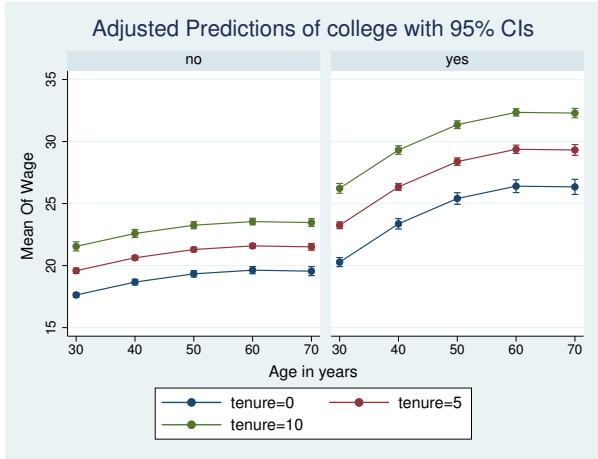
Is this effect constant for everyone? Let's approach that question by first profiling expected wages for some representative values of age and tenure. We can ask `margins` to do that by typing

```
. margins college, predict(base(college=1)) vce(unconditional)
> at(age=(30(10)70) tenure=(0 5 10) peduc=2)
  (output omitted)
```

We used the `at()` option to request values of age from 30 to 70 in units of 10 years and, for each of those ages, tenures of 0, 5, and 10. We also requested `college` $= 0$ and `college` $= 1$, but we did that by typing `college` right after the `margins` command. We could have instead typed `college=(0 1)` in our `at()` option, but this is better. You will see that in a minute. We still want estimates for those who chose to go to college and graduated, so we specify `predict(base(college=1))`. That means we are further conditioning on the unobservable factors that increased the probability of graduating from college.

If you run the `margins` command, you will see that it takes a few seconds and that it produces a lot of output. Let's graph the results,

```
. marginsplot, by(college)
```



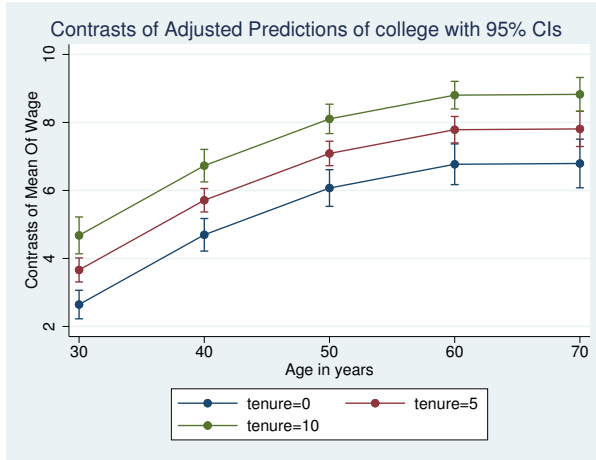
The first thing we notice is that these results are far too regular, and we should review our data collection process. That aside, the age–earnings profiles on the left, where we have taken the degrees away from our college graduates, are distinctly different from those on the right, where they get to retain their degrees. We see that tenure does have an effect, and if we look closely, it has a larger effect on college graduates: the profiles are further apart on the right. What do the points on this graph represent? Each point in the panel on the right is the expected wage for someone who graduated from college, whose parents graduated from college, and who has the age and tenure shown on the graph. Each point on the left is a counterfactual where we assume those same people did not graduate from college but where we continue to condition on the fact that their endogenous choice was to attend and complete college.

Seeing that, we have to ask, what are the profiles of the effect of college? To find those, we just add an `r.` to `college` on our previous `margins` command. Now you know why we specified `college` the way we did.

```
. margins r.college, predict(base(college=1)) vce(unconditional)
> at(age=(30(10)70) tenure=(0 5 10) peduc=2)
  (output omitted)
```

Again, the output is long, so we graph the results.

```
. marginsplot
```



College affects wages the least when people are young and have no tenure. The largest effects are seen for those older than 50 and even more so when they also have long tenure. Each point represents the expected increase in wages due to graduating from college among those who chose to attend college and graduated. So each is an average treatment effect on the treated (ATET). Unlike overall average ATETs, these are conditioned on being at a specific age and having a specific tenure. Each point is bracketed by a pointwise 95% confidence interval. The confidence intervals reveal that we have pretty tight estimates for each of the ATETs. Note that the previous graph also displayed 95% confidence intervals. They were just so narrow that they are difficult to see.

Some might quibble with the "A" we just used in ATET because we have specified values for every covariate. Even so, taking the expectation over the errors in the model is a form of averaging. If you prefer call them the expected TETs (treatment effects on the treated).

We have focused on treatment effects on the treated, those who graduated from college. We could have just as easily asked about treatment effects on the untreated, those who did not graduate from college. What would we expect wages to do if they did graduate from college? Maybe we could reduce the cost of admission or otherwise affect their decision or institute mandatory college attendance. It is a minor change to what we have already typed. In each case, just change

```
predict(base(college=1))
```

to

```
predict(base(college=0))
```

If you do that, you will be conditioning on a decision not to attend college or a failure to complete college. If you make this change and reproduce the first graph, you will find that even after one graduates from college, wages are expected to be a little lower for this group. Recall that the unobserved factors that affected choosing to attend college were positively correlated with wages in both treatment groups.

We gave parents' education short shrift in our analysis, locking it at the single value representing undergraduate degree. You can easily explore how differing levels of parents' education affect the results. Try typing

```
margins college, predict(base(college=1)) vce(unconditional)    ///
        at(age=36 tenure=10 peduc=(1 2 3 4))
```

You will find that parents' education does affect expected wages through the correlation between our two equations.

As is often the case with models having complications, estimation is just the first step.

See *Treatment* under *Methods and formulas* in [ERM] **eregress** and *Estimating treatment effects with margins* in [R] **margins, contrast** for additional information about calculating the ATET.

Video example

Extended regression models: Nonrandom treatment assignment

Also see

[ERM] **eregress** — Extended linear regression

[ERM] **eregress postestimation** — Postestimation tools for eregress

[ERM] **estat teffects** — Average treatment effects for extended regression models

[ERM] **intro 8** — Conceptual introduction via worked example