

Intro 9 — Conceptual introduction via worked example[Description](#)[Remarks and examples](#)[References](#)[Also see](#)

Description

This entry introduces the concepts of endogenous covariates, nonrandom treatment assignment, and endogenous sample selection through a series of examples. It also provides an overview of how to interpret the results of ERMs.

Remarks and examples

stata.com

Remarks are presented under the following headings:

[*Introduction*](#)[*Complications*](#)[*Endogenous covariates*](#)[*Nonrandom treatment assignment*](#)[*Endogenous sample selection*](#)[*Interpreting effects*](#)[*Video examples*](#)

Introduction

In a perfect research world, several assumptions we conventionally make about our data and the data-collection process would be true. For example, we could gather data about all the variables that influence the outcome we want to study. These data would be collected on a random sample of the population of interest. Any inferences we made about a relationship between the dependent variable and an independent variable when studying one group would be just as valid if we studied this group again at a different time or even if we conducted the study for a different group.

Often, applied research is complicated when one or more of the classical assumptions are not true. For example, data on key variables of interest may be unavailable. Our interest may lie in a treatment that cannot be randomly assigned or may be endogenous. Or the subjects we have available to study are not representative of the population we want to study.

When any of these things is true, we cannot make accurate inferences using standard regression methods. Stata provides many commands that can be used when one of these complications occurs. The ERM commands allow you to address these problems in isolation and, more importantly, in combination—as they often occur.

Imagine that a large company is considering offering a workplace wellness program to its employees to help them lose weight. They have conducted a pilot study at one location, and all other locations are expected to be similar. In our dataset, the `wellpgm` variable records whether a given employee participated. After one year, the company wants to know whether the program was effective. Our outcome of interest is weight lost in kilograms. We have called this `weightloss0` to distinguish it from the observed `weightloss` later.

In our fictional data, the number of kilograms lost is also determined by the employee's age in years (`age`), the employee's sex (`sex`), and the employee's starting weight in kilograms (`weight`). Because this is an entirely fictitious example, we have a true measure of willingness to engage in healthy behaviors (`health`).

More formally, in our simulated data, the process that determines weight lost is

$$\text{weightloss0}_i = -4 - 0.1 \times \text{age}_i - 1.5 \times \text{sex}_i + 0.14 \times \text{weight}_i + 1.2 \times \text{wellpgm}_i + 0.5 \times \text{health}_i + u_i$$

Suppose that we are in the situation described above. We observed complete information for all variables for all employees, and participation in the wellness program was unrelated to any employee attributes that we could not observe. In this case, we could fit our model by typing

```
. use https://www.stata-press.com/data/r17/wellness
(Fictional workplace wellness data)
. regress weightloss0 age i.sex weight i.wellpgm health
```

Source	SS	df	MS	Number of obs	=	545
Model	2417.76071	5	483.552141	F(5, 539)	=	589.61
Residual	442.044242	539	.820119187	Prob > F	=	0.0000
				R-squared	=	0.8454
				Adj R-squared	=	0.8440
Total	2859.80495	544	5.25699439	Root MSE	=	.9056

weightloss0	Coefficient	Std. err.	t	P> t	[95% conf. interval]	
age	-.0991644	.0038045	-26.06	0.000	-.1066378	-.0916909
sex						
male	-1.481883	.0937504	-15.81	0.000	-1.666044	-1.297722
weight	.1359547	.0054405	24.99	0.000	.1252676	.1466419
wellpgm						
yes	1.254928	.1076792	11.65	0.000	1.043406	1.46645
health	.4814308	.0255931	18.81	0.000	.4311564	.5317053
_cons	-3.754726	.4432054	-8.47	0.000	-4.625348	-2.884105

```
. estimates store true
```

From this model, we can estimate the average treatment effect (ATE) of the wellness program by using the coefficient on `wellpgm`. We estimate that the ATE is 1.25 kg. In other words, the average weight lost over the course of the year would be 1.25 kg greater if all the company's employees participated in the program versus if no employees participated.

Because we simulated these data, we can confirm that all the confidence intervals contain the true values. If we continued to add more observations, our point estimates would become closer and closer to the real values. This is true because the coefficient estimates shown above are consistent. Because they are consistent, we can make inferences about the effects of each variable on the outcome. We `estimates store` these values as `true` for comparison with later models.

Complications

As discussed in [ERM] [Intro 3](#), a covariate is endogenous if it is correlated with the error term. Practically, this correlation arises for many reasons. For example, we may have omitted an important variable from our model that is correlated with a variable that we included, as we did here. Or we may not have accurately measured one of the covariates in our model. We could also have the case where a variable in the model and the outcome of interest are partially determined by the same unobserved factors. For concreteness, we focus on the role of a single omitted variable in this conceptual introduction.

Often in observational research, the treatment (participation in the wellness program) was not randomly assigned. As discussed in [ERM] Intro 5, we might be able to ignore this issue if we do not suspect that unobserved factors that affect participation also affect the amount of weight loss. However, in this case, we believe participation in the wellness program is also likely to be determined by factors we cannot observe, such as the now-omitted `health` variable.

Further, suppose that the pilot study was structured such that baseline information about all employees was collected at a mandatory benefits meeting at the start of the year. At the end of the year, all employees were asked to go to the company gym during business hours to have their year-end weight recorded, regardless of program participation. Because employees were not required to have their final weight recorded, we observe only the weight of employees who voluntarily went to the gym. We have a selected sample in this case.

Whether an employee is observed in the study could be correlated with unobserved factors that also determine how much weight he or she lost. For example, employees with high values of the now-omitted `health` variable may have generally better diet and exercise habits (independent of the wellness program), leading to higher weight loss. Let's say that for bragging rights, they want to have their superior weight loss recorded, so they are more likely to show up at the end of the year. As discussed in [ERM] Intro 4, if selection is related to unobserved factors that are correlated with the outcome, it cannot be ignored.

If we ignore all of these potential complications, we might erroneously fit the model below. In this model, we omit `health`, and `weightloss` records the observed weight loss only for employees who went to the gym at the end of the year.

$$\text{weightloss}_i = \beta_1 \times \text{age}_i + \beta_2 \times \text{sex}_i + \beta_3 \times \text{weight}_i + \beta_4 \times \text{wellpgm}_i + u_i$$

As before, we could fit the model using `regress`.

```
. regress weightloss age i.sex weight i.wellpgm
```

Source	SS	df	MS	Number of obs	=	337
Model	1239.17345	4	309.793362	F(4, 332)	=	219.74
Residual	468.060374	332	1.4098204	Prob > F	=	0.0000
				R-squared	=	0.7258
				Adj R-squared	=	0.7225
Total	1707.23382	336	5.08105304	Root MSE	=	1.1874

weightloss	Coefficient	Std. err.	t	P> t	[95% conf. interval]
age	-.0800928	.0063184	-12.68	0.000	-.0925219 -.0676637
sex					
male	-1.023886	.146934	-6.97	0.000	-1.312925 -.734847
weight	.0803689	.0074025	10.86	0.000	.0658072 .0949305
wellpgm					
yes	1.913531	.1596906	11.98	0.000	1.599398 2.227664
_cons	-.3699558	.6741312	-0.55	0.584	-1.696063 .9561513

None of the confidence intervals for our coefficient estimates contain the true values. We store the estimates so that we can compare them with estimates from other models later.

```
. estimates store base
```

Endogenous covariates

Continuing with our example, we suspect that `weight` is endogenous now that we cannot observe `health`. Employees who are predisposed to healthy behaviors will likely have a lower starting weight, and this could influence how much weight they lose over the course of the year-long study. If we have a suitable model for how `weight` relates to the unobserved `health`, we can still estimate the parameters consistently.

Let's suppose we believe that the employee's starting weight is a function of the employee's sex and the number of times the employee visits the company gym. We measure gym use as the employee's average number of visits per month to the company gym before the program (`gym`). This will be an instrumental variable for `weight`. Instrumental variables are exogenous covariates that are correlated with the endogenous covariate, not directly related to the outcome, and not correlated with the unobserved error. Because we are using preprogram gym use, we do not expect it to be related to weight loss during the year of the program.

We fit the model using `eregress`, storing the estimates for later comparison.

```
. eregress weightloss age i.sex i.wellpgm, endogenous(weight = i.sex gym)
(output omitted)
. estimates store endog
```

Now, we view and compare the results from each of the commands. We focus on the coefficients here because our interest lies in illustrating how the point estimates change as we address different complications. At the end of the introduction, we show the full output of `eregress` and discuss its interpretation.

```
. estimates table true base endog, stats(N) equations(1) keep(#1:)
```

Variable	true	base	endog
age	-.09916437	-.08009282	-.07964086
sex			
male	-1.481883	-1.023886	-1.6411717
weight	.13595472	.08036889	.14701973
wellpgm			
yes	1.2549281	1.9135311	1.9008534
health	.48143082		
_cons	-3.7547263	-.36995584	-5.5172377
N	545	337	337

Once we account for the endogeneity of `weight`, the coefficients for `sex` and `weight` are close to those of the `true` model and have the correct signs. The estimates for `age` and `wellpgm`, however, are close to each other in the `base` and `endog` models but not close to the `true` values. Our estimates remain inconsistent because we have not yet addressed the endogeneity of the `wellpgm` program indicator.

Endogenous covariates in ERMs need not be continuous. We could instead have an endogenous binary or ordinal covariate. To address the endogeneity of `wellpgm`, we could include an additional model by adding another `endogenous()` option; see [ERM] [Intro 3](#) for more on specifying models with different types of endogenous covariates. Another way to approach the analysis of binary and ordinal endogenous covariates is in the potential-outcomes framework.

Nonrandom treatment assignment

Treatment-effect regressions model the effect of a discrete treatment or intervention on the outcome. In observational data, we cannot randomly assign a treatment of interest to individuals. Treatment status may be related to other covariates that we measure. It may even be related to the unobserved factors that affect the outcome and be endogenous. We cannot just take the sample means of the treated and untreated to estimate the ATE. Instead, we can use the potential-outcomes framework to estimate a treatment effect.

In the potential-outcomes framework, the treatment effect is the difference between the outcome that would occur when a given subject receives the treatment and the outcome that would occur when the subject receives the control instead. We only observe the potential outcome associated with that subject's observed treatment value (either treated or control). However, we can estimate both potential outcomes, conditional on covariates, by using information from the model. For more information about the potential-outcomes framework, see [TE] [teffects intro advanced](#).

The ERM commands may be used with an exogenous or endogenous treatment where the treatment variable is binary or ordinal.

To address the endogenous selection of participation in the wellness program, we need a model for `wellpgm`. Whether the employee was a smoker at the beginning of the year (`smoke`) is an additional covariate in our treatment model. Because smoking signals a lower willingness to engage in healthy behaviors, it should be correlated with participation in the program, but smoking status measured before the program was offered should not be independently associated with weight loss during the program.

```
. eregress weightloss age i.sex, endogenous(weight = i.sex gym)
> entreat(wellpgm = age i.smoke, nointeract)
(output omitted)
. estimates store entrtr
```

By specifying `nointeract`, we keep the same coefficients for both treatment groups in the main equation. This is not the most common approach. However, we simulated the data this way to keep the `estimates` table results compact and easy to compare across models. We will show you a more interesting model later.

Now, we view and compare the results for the main equation for each of the models.

```
. estimates table true base endog entrtr, stats(N) equations(1) keep(#1:)
```

Variable	true	base	endog	entrtr
age	-.09916437	-.08009282	-.07964086	-.10430319
sex male	-1.481883	-1.023886	-1.6411717	-1.5995888
weight	.13595472	.08036889	.14701973	.14151952
wellpgm yes	1.2549281	1.9135311	1.9008534	.83556752
health _cons	.48143082 -3.7547263	-.36995584	-5.5172377	-3.488841
N	545	337	337	337

In the `entrtr` model, where we have accounted for the endogeneity of starting weight and the endogenous treatment assignment to the wellness program, we estimate that the effect of participating

in the program is 0.84 kg lost. This is closer to the 1.25 kg we estimated in the `true` model than the 1.90 kg we estimated in the `endog` model that did not account for treatment assignment.

Endogenous sample selection

Sample selection is an ambiguous term because different authors have used it to mean different things. To add more ambiguity, sample selection has been equated with nonresponse bias and selection bias in some disciplines. Much of the ambiguity arises from authors not being precise about when sample selection is ignorable.

Sample selection is like treatment assignment: a process maps each individual into or out of the sample. This process depends on observable covariates and unobservable factors. When unobservable factors that affect who is in the sample are independent of unobservable factors that affect the outcome, then the sample selection is not endogenous. In this case, the sample selection is ignorable—our estimator that ignores sample selection is still consistent.

In contrast, when the unobservable factors that affect who is included in the sample are correlated with the unobservable factors that affect the outcome, the sample selection is endogenous and it is not ignorable, because estimators that ignore endogenous sample selection are not consistent.

The ERM commands may be used with endogenous sample selection with a probit or tobit selection model. A probit selection model is used when we have a binary indicator of selection. A tobit selection model is used when we have a continuous indicator for selection.

We suspect that unobserved factors that influence whether employees came to the gym for the year-end weigh-in also influence the amount of weight lost. In other words, we believe we may have endogenous sample selection. Our `true` model included all information on all 545 employees. In reality, only 337 completed the final weigh-in for our study. However, we still want to know what the potential effect of the program was for all employees. The 0.84 kg that we estimated in *Nonrandom treatment assignment* is not a consistent estimate of the program's ATE in the company if the 337 employees in our study are not representative of the population.

By modeling the sample-selection process, we can include all 545 employees in our estimation sample. The variable `completed` indicates whether the employee completed the final weigh-in. Employees with `completed = 0` have missing values for `weightloss`. However, because all other data were gathered at a mandatory meeting at the start of the year (such as starting weight) or collected from administrative records (such as prior-year visits to the company gym), we have complete information for all other variables.

We include the employee's job classification (`salaried`) and years employed at the company (`experience`) as additional covariates in our selection model that are excluded from the main equation. `salaried` is 1 if the employee is salaried and is 0 if the employee is paid hourly. We anticipate that salaried employees will have more opportunity to visit the gym during the day and that employees who have been with the company longer will be more motivated to help complete the study. Aside from their effect on completing the weigh-in, we do not believe that `salaried` or `experience` have any direct effect on `weightloss`.

We fit our model, accounting for the potentially endogenous selection.

```
. eregress weightloss age i.sex, endogenous(weight = i.sex gym)
> entreat(wellpgm = age i.smoke, nointeract)
> select(completed = i.wellpgm experience i.salaried)
(output omitted)
. estimates store endsel
```

Then, we compare these estimates with those from our previous models.

```
. estimates table true base endog entrtr endsel, stats(N) equations(1) keep(#1:)
```

Variable	true	base	endog	entrtr	endsel
age	-.09916437	-.08009282	-.07964086	-.10430319	-.11149981
sex male	-1.481883	-1.023886	-1.6411717	-1.5995888	-1.5607651
weight	.13595472	.08036889	.14701973	.14151952	.14353999
wellpgm yes	1.2549281	1.9135311	1.9008534	.83556752	.92462755
health _cons	.48143082 -3.7547263	-.36995584	-5.5172377	-3.488841	-3.6798876
N	545	337	337	337	545

After accounting for the potentially endogenous selection that occurs because some employees chose not to complete the final weigh-in, we see that our estimated ATE is 0.925, which is closer to its true value than in the models that did not address selection.

Interpreting effects

In the previous sections, we showed only the coefficient estimates from the main outcome equation. The full output for `eregress` and the other ERM commands includes estimates of coefficients of covariates in the auxiliary models, error variances, and error correlation terms.

For many models, the coefficient estimates themselves are not directly useful. You will need to use `margins` or `estat teffects` to obtain interpretable effects. However, the correlation estimates always provide relevant information.

The full results for the last `eregress` command that we estimated are as follows:

8 Intro 9 — Conceptual introduction via worked example

```
. eregress weightloss age i.sex, endogenous(weight = i.sex gym)
> entreat(wellpgm = age i.smoke, nointeract)
> select(completed = i.wellpgm experience i.salaried)

(iteration log omitted)
```

Extended linear regression

Number of obs = 545
 Selected = 337
 Nonselected = 208

Log likelihood = -2800.8318

Wald chi2(4) = 749.04
 Prob > chi2 = 0.0000

	Coefficient	Std. err.	z	P> z	[95% conf. interval]	
weightloss						
age	-.1114998	.0083531	-13.35	0.000	-.1278715	-.0951281
sex						
male	-1.560765	.2062746	-7.57	0.000	-1.965056	-1.156474
weight	.14354	.0175073	8.20	0.000	.1092263	.1778537
wellpgm						
yes	.9246275	.2750269	3.36	0.001	.3855848	1.46367
_cons	-3.679888	1.464123	-2.51	0.012	-6.549515	-.81026
completed						
wellpgm						
yes	.6553902	.2263862	2.90	0.004	.2116814	1.099099
experience	-.8153984	.0617977	-13.19	0.000	-.9365196	-.6942772
salaried						
yes	.4709859	.1419878	3.32	0.001	.192695	.7492768
_cons	4.902936	.3973849	12.34	0.000	4.124076	5.681796
wellpgm						
age	-.0938617	.0072734	-12.90	0.000	-.1081173	-.079606
smoke						
yes	-1.477078	.1772103	-8.34	0.000	-1.824404	-1.129752
_cons	4.228481	.337379	12.53	0.000	3.56723	4.889732
weight						
sex						
male	9.506396	.6960864	13.66	0.000	8.142091	10.8707
gym	-.8184902	.0779351	-10.50	0.000	-.9712401	-.6657402
_cons	80.10245	.5407952	148.12	0.000	79.04251	81.16239
var(e.weig~s)	2.015328	.263477			1.559777	2.603927
var(e.weight)	65.98395	3.997213			58.59678	74.30241
corr(e.com~d, e.weightloss)	.5434105	.0824836	6.59	0.000	.362338	.6849556
corr(e.wel~m, e.weightloss)	.5878321	.1054098	5.58	0.000	.3440372	.7573749
corr(e.wei~t, e.weightloss)	-.4801763	.089175	-5.38	0.000	-.6353685	-.2877017
corr(e.wel~m, e.completed)	.3753168	.1523364	2.46	0.014	.0470351	.6304273
corr(e.wei~t, e.completed)	-.0643813	.0718768	-0.90	0.370	-.2030702	.0768401
corr(e.wei~t, e.wellpgm)	-.096324	.0691411	-1.39	0.164	-.2292586	.0401382

The `completed`, `wellpgm`, and `weight` equations provide the coefficient estimates for the auxiliary endogenous selection, treatment assignment, and endogenous covariate models.

The correlation estimates tell us about the endogeneity in our model. For example, we speculated that we might have endogenous selection. The error correlation `corr(e.completed, e.weightloss)` is an estimate of the correlation between the error from the selection equation and the error from the outcome equation. The estimate is significant, so we reject the hypothesis that there is no endogenous selection. It is positive, so we conclude that unobserved factors that increase the likelihood of being in the sample tend to occur with unobserved factors that increase the amount of weight lost. Looking at the other correlations, we find that our suspicions of endogenous treatment choice and the endogeneity of initial weight are likewise confirmed.

We estimated an ATE in our running example. In our simple illustration, we were able to use the coefficient on `wellpgm`. If `wellpgm` had been interacted with other covariates in the model, we would have needed to use `estat teffects`. We also could have estimated the effect of the wellness program on just those employees who participated, the *average treatment effect on the treated* (ATET).

Using this regression, if we ask questions about how participating in `wellpgm` affects the expected change in `weightloss`, we will almost always get the same answer: 0.92 kg greater weight loss with the program than without. That is the coefficient on `wellpgm` in the main outcome equation. This model is linear and contains no interactions between the treatment and other covariates. So, whether we ask about the ATE or the ATET, the answer is 0.92. Whether we ask about the expected additional `weightloss` for a person who chose to participate or about all the women who chose to participate, the answer is the same. No matter what, the expected change is always 0.92.

To make this interesting, we will need a more complex model. We could take the `nointeract` suboption off the `entreat()` option. If we did that and refit the model, all the questions above would produce different answers. But, as we said, our data are simulated with no interaction. So let's use another artifice.

Let's assume that the clerk in charge of the final weigh-in overheard management discussing the new program. The managers seemed particularly interested in participants losing at least 4 kg (8.8 pounds). Thinking he was being helpful, our clerk decided to save everyone some effort and did not record actual weights. Instead, he recorded only whether employees were at least 4 kg lighter than they had been at the initial weigh-in.

We can no longer analyze weight loss, but we can analyze the probability of losing at least 4 kg. We fit the same full model but this time use `eprobit`, and our dependent variable becomes `lost4`, which is 0 if the employee lost less than 4 kg and is 1 if the employee lost 4 kg or more.

```
. eprobit lost4 age i.sex, endogenous(weight = i.sex gym)
> entreat(wellpgm = age i.smoke, nointeract)
> select(completed = i.wellpgm experience i.salaried) vce(robust)

(iteration log omitted)
```

Extended probit regression Number of obs = 545
Selected = 337
Nonselected = 208

Log pseudolikelihood = -2392.5364 Wald chi2(4) = 184.27
Prob > chi2 = 0.0000

	Coefficient	Robust std. err.	z	P> z	[95% conf. interval]	
lost4						
age	-.0461113	.0129744	-3.55	0.000	-.0715406	-.020682
sex						
male	-1.192968	.1806428	-6.60	0.000	-1.547022	-.8389148
weight	.1131467	.0108868	10.39	0.000	.0918089	.1344844
wellpgm						
yes	1.370215	.4048158	3.38	0.001	.5767905	2.163639
_cons	-8.034426	1.199574	-6.70	0.000	-10.38555	-5.683305
completed						
wellpgm						
yes	.6534203	.2310957	2.83	0.005	.200481	1.10636
experience	-.801973	.0676059	-11.86	0.000	-.9344781	-.6694679
salaried						
yes	.3955088	.1549943	2.55	0.011	.0917255	.6992921
_cons	4.862419	.4186367	11.61	0.000	4.041906	5.682932
wellpgm						
age	-.0958611	.0071251	-13.45	0.000	-.109826	-.0818963
smoke						
yes	-1.515911	.1754356	-8.64	0.000	-1.859758	-1.172063
_cons	4.310847	.338842	12.72	0.000	3.646728	4.974965
weight						
sex						
male	9.501602	.6983151	13.61	0.000	8.13293	10.87028
gym	-.8162669	.0765488	-10.66	0.000	-.9662998	-.666234
_cons	80.09771	.5302486	151.06	0.000	79.05844	81.13697
var(e.weight)	65.98399	3.805168			58.93203	73.8798
corr(e.com~d, e.lost4)						
corr(e.wel~m, e.lost4)	.5236573	.1297834	4.03	0.000	.2268709	.7314522
corr(e.wel~m, e.lost4)						
corr(e.wei~t, e.lost4)	.249717	.2438804	1.02	0.306	-.2493086	.6439525
corr(e.wel~m, e.completed)						
corr(e.wei~t, e.completed)	-.6846067	.096236	-7.11	0.000	-.8314263	-.448426
corr(e.wei~t, e.completed)						
corr(e.wel~m, e.completed)	.3678357	.1636913	2.25	0.025	.014886	.6392761
corr(e.wei~t, e.wellpgm)						
corr(e.wel~m, e.wellpgm)	-.0821217	.074566	-1.10	0.271	-.2255026	.0647412
corr(e.wei~t, e.wellpgm)	-.0888819	.0671873	-1.32	0.186	-.218281	.0435887

These parameter estimates are pretty close to those from running `eregress` on `weightloss`. But unless you like thinking in terms of shifts along a standardized normal distribution, the coefficient of 1.37 on `wellpgm` is difficult to interpret. We still know that the effect of the program is statistically significant, but little more.

Note that we added `vce(robust)`. This will allow us to treat our sample as a draw from a population when using `estat teffects` and `margins` and thus make inferences about the population. Otherwise, we would be taking the sample as fixed and not as a draw from a population.

If management is thinking about expanding the program, they will want to evaluate its effectiveness. What proportion of employees across all facilities would lose 4 kg or more naturally, either through all employees not participating or through the program simply not being offered? What proportion would lose 4 kg or more if all employees participated? `estat teffects` will estimate these proportions when we request potential-outcome means.

```
. estat teffects, pomean
Predictive margins                                     Number of obs = 545
```

		Unconditional		z	P> z	[95% conf. interval]	
		Margin	std. err.				
P0mean							
	wellpgm						
	no	.0844851	.0431001	1.96	0.050	.0000106	.1689597
	yes	.4702298	.086969	5.41	0.000	.2997736	.640686

About 47% are expected to lose 4 kg if everyone participates compared with only 8% when no one participates. More to the point, what is the difference in those averages? We type

```
. estat teffects
Predictive margins                                     Number of obs = 545
```

		Unconditional		z	P> z	[95% conf. interval]	
		Margin	std. err.				
ATE							
	wellpgm						
	(yes vs no)	.3857447	.1226037	3.15	0.002	.1454458	.6260436

The proportion of employees who would be expected to lose 4 kg increases by 0.39 if everyone participates in the program versus if no one participates; that is the ATE.

What if we consider only program participants? What is the expected average increase in the proportion losing 4 kg? Let's estimate the expected effect of the wellness program on just those employees who choose to participate, the ATET.

```
. estat teffects, atet
Predictive margins                                     Number of obs = 545
                                                       Subpop. no. obs = 208
```

		Unconditional		z	P> z	[95% conf. interval]	
		Margin	std. err.				
ATET							
	wellpgm						
	(yes vs no)	.5335926	.1098873	4.86	0.000	.3182174	.7489678

The ATET of 0.53 implies that the program is expected to increase the proportion of employees who lose 4 kg by 0.53 among those who choose to participate across all facilities. Recall that we believed success in the program would be positively correlated with employees' decision to participate. That is what made the decision endogenous. It is not surprising that we expect better results for participants than we do for all the employees as a whole.

We are going to need margins to answer some other questions, so let's introduce it by reestimating the ATET.

```
. margins r(0 1).wellpgm if wellpgm, contrast(effects nowald)
Contrasts of predictive margins                                Number of obs = 208
Model VCE: Robust
Expression: Average structural function probability, predict()
```

	Delta-method		z	P> z	[95% conf. interval]	
	Contrast	std. err.				
wellpgm (yes vs no)	.5335926	.109483	4.87	0.000	.3190099	.7481752

We have reproduced the estimate.

There is a lot happening in that `margins` command.

`r(0 1).wellpgm` tells `margins` to form two counterfactuals—one at `wellpgm=0` and another at `wellpgm=1`—and to then take the reference (`r`) contrast (difference) of those two counterfactuals.

if `wellpgm` restricts the sample to those who participated in the wellness program.

`contrast(effects nowald)` tells `margins` to report the z statistic and probability $> z$, which are not shown by default. It also tells `margins` to suppress the overall Wald statistic.

The standard errors are slightly smaller than those from `estat teffects`. If we wanted them to match exactly, we would use the `vce(unconditional)` option with `margins`. That option creates standard errors appropriate to make inferences about the population. The standard errors are so close that we will dispense with `vce(unconditional)` in this section.

Now, let's ask a series of different questions from a different perspective.

The physical trainer for our fictional company is having lunch with a new employee, Betty. The trainer mentions the wellness program, and Betty asks if it is likely to do her much good. Betty looks to be mid thirties and average weight. She says she goes to the gym a couple of times a month. The trainer recalls people with those characteristics doing well with the program. Betty's data are already in the company's database, so the trainer opens Stata on her laptop and types

```
. margins r(0 1).wellpgm if name=="Betty", contrast(effects nowald) noesample
warning: prediction constant over observations.
Contrasts of predictive margins                                Number of obs = 1
Model VCE: Robust
Expression: Average structural function probability, predict()
```

	Delta-method		z	P> z	[95% conf. interval]	
	Contrast	std. err.				
wellpgm (yes vs no)	.5894013	.222732	2.65	0.008	.1528545	1.025948

The trainer tells Betty that employees with her characteristics increase their chances of losing 4 kg by about 59 percentage points when they are in the program.

Later, another new employee, Fred, asks whether the program is likely to help him lose that last few kilograms. He is thin, in his upper fifties, and he already goes to the gym about twice a week. Our trainer types

```
. margins r(0 1).wellpgm if name=="Fred", contrast(effects nowald) noesample
warning: prediction constant over observations.
Contrasts of predictive margins                                Number of obs = 1
Model VCE: Robust
Expression: Average structural function probability, predict()
```

	Delta-method		z	P> z	[95% conf. interval]	
	Contrast	std. err.				
wellpgm (yes vs no)	.0147468	.0226186	0.65	0.514	-.0295849	.0590785

She tells Fred that the program might be good for him but not to expect it to create much weight loss. Fred says he would like to sign up, just so he can meet some other employees.

When Fred leaves, our trainer calls her office mate and makes a wager that Fred will not lose 4 kg on the program. The trainer then realizes that she placed a bet on overall weight loss, not just the loss attributable to the wellness program. To be certain, she checks the potential outcomes of weight loss for Fred being in the program and for Fred being out of the program.

```
. margins i(0 1).wellpgm if name=="Fred", noesample
warning: prediction constant over observations.
Predictive margins                                            Number of obs = 1
Model VCE: Robust
Expression: Average structural function probability, predict()
```

	Delta-method		z	P> z	[95% conf. interval]	
	Margin	std. err.				
wellpgm no	.0000218	.0000382	0.57	0.569	-.0000532	.0000967
yes	.0147686	.022641	0.65	0.514	-.029607	.0591441

With a negligible chance of losing 4 kg if Fred chooses not to participate and a slim 1.5% chance if Fred does participate, our trainer feels pretty good about her wager. Even the upper bound of the confidence intervals makes the trainer confident. Of course, these are the expected results for all employees with Fred's characteristics; Fred might be an overachiever.

The counterfactuals and contrasts that we computed for Betty and Fred are the expected values from our model conditioned on the exogenous covariates in the main equation, `age` and `sex`, on the level of endogeneity for the endogenous equations for `weight` and `wellpgm`, and on fixing the values of `wellpgm` first to 0 and then to 1. The estimates for Betty are what we would expect if we averaged over hundreds of employees who match Betty’s `age`, `sex`, and level of endogeneity. The same applies to Fred.

Also note that we typed `r(0 1)`, rather than just `r.` That is because we are operating on a single observation, and `margins` cannot determine the appropriate levels of `wellpgm` for which to form counterfactuals. We had to tell `margins` to use 0 and 1.

It is unlikely that our trainer has Stata on her laptop or has the inclination to type `margins` commands. As analysts, however, we might create a table for her that she can use to assess candidates and help employees form realistic expectations.

Our dataset already has grouping variables for `age`, `gym`, `weight`, and `sex`. We can estimate the expected additional probability of losing more than 4 kg for each combination of these groups by using an `over()` option.

```
. margins r.wellpgm, contrast(effects nowald) over(agegrp gymgrp wtgrp sex)
Contrasts of predictive margins                               Number of obs = 545
Model VCE: Robust
Expression: Average structural function probability, predict()
Over:           agegrp gymgrp wtgrp sex
```

	Delta-method		z	P> z	[95% conf. interval]	
	Contrast	std. err.				
wellpgm@ agegrp# gymgrp# wtgrp#sex (yes vs no) 20-29 0						
< 60 female (yes vs no) 20-29 0	0	(omitted)				
< 60 male (yes vs no) 20-29 0	0	(omitted)				
60-69 female (yes vs no) 20-29 0	.6437056	.1621665	3.97	0.000	.325865	.9615462
60-69 male (output omitted)	0	(omitted)				

Those rows marked (omitted) represent combinations of characteristics for which we do not have any employees in our sample. We could use our model to extrapolate to those groups, but we are not going to do that. What we do have for each combination of groups is an estimate of the expected increase in the probability of losing 4 kg, a test that the probability is greater than 0, and a 95% confidence interval.

Those results will take a lot of transcription to create something compact for the trainer. And while our hearts are warmed by the tests and confidence intervals, the trainer might not feel the same way. If we wanted to be exceptionally helpful, we could build a table manually showing ATEs for each group.

```
. predict te, te
. table (agegrp gymgrp) (sex wtgrp), statistic(mean te) nformat(%4.2f) nototals
```

	Employee sex; 0=female, 1=male								
	female					male			
	Weight groups								
	< 60	60-69	70-79	80-89	90 up	60-69	70-79	80-89	90 up
Age groups									
20-29									
Gym visit groups									
0		0.64	0.58	0.53	0.41		0.63	0.62	0.52
0-5		0.65	0.63	0.57			0.64	0.65	0.59
6-10		0.51	0.64	0.65			0.55	0.58	0.64
11 up		0.40					0.35		
30-39									
Gym visit groups									
0	0.48		0.65	0.62	0.61		0.61	0.65	0.62
0-5		0.48	0.64	0.64				0.56	0.62
6-10	0.21	0.39	0.54	0.60		0.27	0.31	0.51	0.48
11 up		0.34	0.43				0.24		0.53
40-49									
Gym visit groups									
0		0.45	0.57	0.62	0.65		0.33	0.50	0.62
0-5		0.39	0.48	0.59	0.61		0.27	0.38	0.55
6-10		0.22	0.33	0.38		0.09	0.14	0.25	0.42
11 up	0.07	0.10		0.28		0.09	0.08	0.19	
50-59									
Gym visit groups									
0		0.26	0.35	0.46	0.62		0.25	0.29	0.47
0-5	0.06		0.22	0.40	0.62		0.12	0.20	0.32
6-10	0.05	0.04	0.22	0.16	0.39		0.05	0.10	0.13
11 up	0.01	0.01	0.05			0.01	0.01		
60 up									
Gym visit groups									
0			0.17	0.25	0.37		0.07	0.12	0.26
0-5			0.07	0.33	0.28	0.02		0.03	0.11
6-10		0.02	0.04	0.10		0.01	0.02	0.03	0.08
11 up	0.00		0.02				0.00	0.02	0.03

We first predicted the expected treatment effects for each observation in our sample. Then, we let `table` average those values for each combination of groups. For any combination of groups, these estimates match those from `estat teffects` for each group.

Here we have demonstrated how you can use `estat teffects` and `margins` to answer a variety of interesting questions after fitting a model with an endogenous covariate, endogenous treatment, and endogenous sample selection. ERMs can address one additional complication—within-panel or within-group correlation—if we fit a random-effects model with `xte regress`, `xte intreg`, `xte probit`, or `xte oprobit`. You can use `estat teffects` and `margins` to interpret results of random-effects models as well. See [ERM] [Example 7](#) and [ERM] [Example 9](#).

Video examples

- Extended regression models, part 4: Interpreting the model
- Extended regression models, part 3: Endogenous sample selection
- Extended regression models, part 2: Nonrandom treatment assignment
- Extended regression models, part 1: Endogenous covariates

References

- Cameron, A. C., and P. K. Trivedi. 2005. *Microeconometrics: Methods and Applications*. New York: Cambridge University Press.
- . 2022. *Microeconometrics Using Stata*. 2nd ed. College Station, TX: Stata Press.
- Gould, W. W. 2018. Ermistatas and Stata's new ERMs commands. *The Stata Blog: Not Elsewhere Classified*. <https://blog.stata.com/2018/03/27/ermistatas-and-statas-new-ermis-commands/>.
- Roodman, D. 2011. Fitting fully observed recursive mixed-process models with `cmp`. *Stata Journal* 11: 159–206.
- Wooldridge, J. M. 2010. *Econometric Analysis of Cross Section and Panel Data*. 2nd ed. Cambridge, MA: MIT Press.

Also see

- [ERM] **Intro 1** — An introduction to the ERM commands
- [ERM] **Intro 7** — Model interpretation
- [ERM] **Glossary**