

Estimating effects from extended regression models

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Extended regression models

Extended regression model (ERM) is a Stata term for a class of regression models

- The outcome can be continuous (linear), probit, ordered probit, or censored (tobit)
- Some of the covariates may be endogenous
 - The endogenous covariates may be continuous, probit, or ordered probit
- Endogenous sample-selection may be modeled
- Exogenous or endogenous treatment assignment may be modeled
- The new-in-Stata-15 commands `eregress`, `eprobit`, `eoprobit`, and `eintreg` fit ERMs

Extended regression models

- Some of the covariates may be endogenous
 - The endogenous covariates may be continuous, binary, or ordinal
 - Polynomial terms and interaction terms constructed from the endogenous covariates are allowed
 - Interactions among the endogenous covariates and interactions between the endogenous covariates and the exogenous covariates are allowed

Outline

- I cannot do justice to ERMs in this short talk
- I discuss examples in which I
 - define some of the terms that I have already used
 - illustrate some command syntax
 - illustrate how to estimate some effects using postestimation commands

- Fictional data on wellness program from large company

```
. use wprogram
```

```
. describe
```

```
Contains data from wprogram.dta
```

```
obs:      3,000
```

```
vars:      6
```

```
size:     72,000
```

```
28 Jul 2017 07:13
```

variable name	storage type	display format	value label	variable label
wchange	float	%9.0g	changel	Weight change level
age	float	%9.0g		Years over 50
over	float	%9.0g		Overweight (tens of pounds)
phealth	float	%9.0g		Prior health score
prog	float	%9.0g	yesno	Participate in wellness program
wtprog	float	%9.0g	yesno	Offered work time to participate in program

```
Sorted by:
```

- Weight change levels and program participation

```
. tabulate wchange prog
```

Weight change level	Participate in wellness program		Total
	No	Yes	
Loss	239	909	1,148
No change	468	605	1,073
Gain	593	186	779
Total	1,300	1,700	3,000

- Program appears to help
- But this data is observational
 - Table does not account for how observed covariates and/or unobserved errors that affect program participation also affect the outcome variable

- If only observed covariates age over and phealth affect program participation and wchange (with or without program), we could use an ordinal probit model

```
. eoprobit wchange prog age over phealth, vsquish nolog
```

```
Extended ordered probit regression          Number of obs      =          3,000
                                           Wald chi2(4)       =          736.09
Log likelihood = -2866.5688                Prob > chi2        =          0.0000
```

wchange	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
prog	-.8668405	.0460018	-18.84	0.000	-.9570023	-.7766787
age	.097322	.0677733	1.44	0.151	-.0355113	.2301552
over	.3433724	.0360858	9.52	0.000	.2726456	.4140992
phealth	-.3983531	.0385081	-10.34	0.000	-.4738276	-.3228786
cut1	-.8871706	.0539205			-.9928528	-.7814885
cut2	.2358913	.0522019			.1335775	.3382051

```
. eoprobit wchange prog age over phealth, vsquish nolog
```

```
Extended ordered probit regression          Number of obs    =      3,000
                                             Wald chi2(4)     =      736.09
Log likelihood = -2866.5688                 Prob > chi2      =      0.0000
```

wchange	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
prog	-.8668405	.0460018	-18.84	0.000	-.9570023	-.7766787
age	.097322	.0677733	1.44	0.151	-.0355113	.2301552
over	.3433724	.0360858	9.52	0.000	.2726456	.4140992
phealth	-.3983531	.0385081	-10.34	0.000	-.4738276	-.3228786
cut1	-.8871706	.0539205			-.9928528	-.7814885
cut2	.2358913	.0522019			.1335775	.3382051

$$\mathbf{x}\beta = \beta_2 \text{age} + \beta_3 \text{over} + \beta_4 \text{phealth}$$

$$\mathbf{w}\beta = \beta_1 \text{prog} + \mathbf{x}\beta$$

$$wchange = \begin{cases} \text{"Loss"} & \text{if } \mathbf{w}\beta + \epsilon \leq cut1 \\ \text{"No change"} & \text{if } cut1 < \mathbf{w}\beta + \epsilon \leq cut2 \\ \text{"Gain"} & \text{if } cut2 < \mathbf{w}\beta + \epsilon \end{cases}$$

$$\mathbf{x}\beta = \beta_2 \text{age} + \beta_3 \text{over} + \beta_4 \text{phealth}$$

$$\mathbf{w}\beta = \beta_1 \text{prog} + \mathbf{x}\beta$$

$$wchange = \begin{cases} \text{"Loss"} & \text{if } \mathbf{w}\beta + \epsilon \leq cut1 \\ \text{"No change"} & \text{if } cut1 < \mathbf{w}\beta + \epsilon \leq cut2 \\ \text{"Gain"} & \text{if } cut2 < \mathbf{w}\beta + \epsilon \end{cases}$$

$\epsilon \sim N(0, 1)$ yields

$$\Pr(wchange = \text{"Loss"}) = \Phi(cut1 - \mathbf{w}\beta)$$

$$\Pr(wchange = \text{"No change"}) = \Phi(cut2 - \mathbf{w}\beta) - \Phi(cut1 - \mathbf{w}\beta)$$

$$\Pr(wchange = \text{"Gain"}) = 1 - \Phi(cut2 - \mathbf{w}\beta)$$

- I want to estimate the how changing prog=0 to prog=1 changes each of the probabilities

$\Pr(\text{wchange} = \text{"Loss"})$

$\Pr(\text{wchange} = \text{"No change"})$

$\Pr(\text{wchange} = \text{"Gain"})$

When I type

`eoprobit wchange prog age over phealth, vsquish nolog`

I am assuming that `prog` is independent of ϵ in

$$wchange = \begin{cases} \text{"Loss"} & \text{if } \beta_1 \text{prog} + \mathbf{x}\boldsymbol{\beta} + \epsilon \leq cut1 \\ \text{"No change"} & \text{if } cut1 < \beta_1 \text{prog} + \mathbf{x}\boldsymbol{\beta} + \epsilon \leq cut2 \\ \text{"Gain"} & \text{if } cut2 < \beta_1 \text{prog} + \mathbf{x}\boldsymbol{\beta} + \epsilon \end{cases}$$

In other words, I am assuming that `prog` is exogenous

If `prog` is not independent of ϵ , `prog` is endogenous

If prog is endogenous, I must model the dependence.

Consider

$$wchange = \begin{cases} \text{"Loss"} & \text{if } \beta_1 prog + \mathbf{x}\boldsymbol{\beta} + \epsilon \leq cut1 \\ \text{"No change"} & \text{if } cut1 < \beta_1 prog + \mathbf{x}\boldsymbol{\beta} + \epsilon \leq cut2 \\ \text{"Gain"} & \text{if } cut2 < \beta_1 prog + \mathbf{x}\boldsymbol{\beta} + \epsilon \end{cases}$$

$$prog = (\mathbf{x}\boldsymbol{\gamma} + \gamma_1 wtime + \eta > 0)$$

ϵ and η are joint normal

$$\mathbf{x}\boldsymbol{\gamma} = \gamma_2 age + \gamma_3 over + \gamma_4 phealth$$

Fit by: eoprobit wchange age over phealth ,

endog(prog = age over phealth wtime, probit)

```

. eoprobit wchange age over phealth , ///
> endog(prog = age over phealth wtprog, probit) ///
> vsquish nolog
Extended ordered probit regression      Number of obs      =      3,000
                                         Wald chi2(4)        =      409.97
Log likelihood = -4401.0952             Prob > chi2         =      0.0000

```

	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
wchange						
age	.2155906	.0705048	3.06	0.002	.0774037	.3537776
over	.4349946	.0387185	11.23	0.000	.3591078	.5108814
phealth	-.4933361	.0411866	-11.98	0.000	-.5740603	-.412612
prog						
Yes	-.3624996	.1031408	-3.51	0.000	-.5646519	-.1603473
prog						
age	-.9341234	.0840002	-11.12	0.000	-1.098761	-.7694861
over	-1.058621	.0514252	-20.59	0.000	-1.159412	-.9578294
phealth	.9001108	.0504804	17.83	0.000	.801171	.9990507
wtprog	1.631615	.0780834	20.90	0.000	1.478574	1.784656
_cons	.0090842	.0535434	0.17	0.865	-.095859	.1140274
/wchange						
cut1	-.5897304	.0781626			-.7429264	-.4365345
cut2	.5029323	.068292			.3690825	.6367821
corr(e.prog, e.wchange)	-.3478179	.0604422	-5.75	0.000	-.4603282	-.2243109

cut2	.5099323	.068292				
corr(e.prog, e.wchange)	-.3478179	.0604422	-5.75	0.000	-.4603282	-.2243109

- The nonzero correlation between e.prog and e.wchange indicates that prog is endogenous
- Those who are more likely to participate are more likely to lose weight

```

. margins r.prog, ///
> predict(fix(prog) outlevel("Loss")) ///
> predict(fix(prog) outlevel("No change")) ///
> predict(fix(prog) outlevel("Gain")) ///
> contrast(nowald)

```

Contrasts of predictive margins

Model VCE : OIM

```

1._predict : Pr(wchange==Loss), predict(fix(prog) outlevel("Loss"))
2._predict : Pr(wchange==No change), predict(fix(prog) outlevel("No
change"))
3._predict : Pr(wchange==Gain), predict(fix(prog) outlevel("Gain"))

```

	Delta-method			
	Contrast	Std. Err.	[95% Conf. Interval]	
prog@_predict				
(Yes vs No) 1	.1259899	.0356631	.0560914	.1958883
(Yes vs No) 2	-.0185024	.0055583	-.0293965	-.0076084
(Yes vs No) 3	-.1074874	.0306512	-.1675628	-.0474121

- When everyone joins the program instead of when no one participants in the program,
 - On average, the probability of “Loss” goes up by .13
 - On average, the probability of “No change” goes down by .02
 - On average, the probability of “Gain” goes down by .11

- `predict(fix(prog))` tells margins to specify `fix(prog)` to predict when computing each predicted probability
- `fix(prog)` causes the value of `prog` not to affect ϵ , even though they are correlated
 - `fix(prog)` specifies that ϵ should be held fixed when `prog` changes
 - `fix(prog)` gets us the effect of the program that is not contaminated by the selection effect/correlation between ϵ and η that increases the participation among people more likely to lose weight

- This type of prediction is sometimes called the structural prediction or an average structural function; see Blundell and Powell (2003), Blundell and Powell (2004), Wooldridge (2010), and Wooldridge (2014),
- The difference between the mean of the average of the structural predictions when $\text{prog}=1$ and the mean of the average of the structural predictions when $\text{prog}=0$ is an average treatment effect (Blundell and Powell (2003) and Wooldridge (2014))

Standard errors for population versus sample

- The delta-method standard errors reported by `margins` hold the covariates fixed at their sample values
 - The delta-method standard errors are for a sample-average treatment effect instead of a population-averaged treatment effect
 - The sample-averaged treatment effect is for those individuals that showed up in that run of the treatment
 - The population-averaged treatment effect is for a random draw of individuals from the population
- To get standard errors for the population-average treatment effect, specify `vce(robust)` to the estimation command and specify `vce(unconditional)` to `margins`

```

. quietly eoprobit wchange age over phealth ,          ///
>     endog(prog = age over phealth wtprog, probit) ///
>     vce(robust)

. margins r.prog,          ///
>     predict(fix(prog) outlevel("Loss"))          ///
>     predict(fix(prog) outlevel("No change"))     ///
>     predict(fix(prog) outlevel("Gain"))          ///
>     contrast(nowald) vce(unconditional)

```

Contrasts of predictive margins

```

1._predict   : Pr(wchange==Loss), predict(fix(prog) outlevel("Loss"))
2._predict   : Pr(wchange==No change), predict(fix(prog) outlevel("No
change"))
3._predict   : Pr(wchange==Gain), predict(fix(prog) outlevel("Gain"))

```

	Unconditional		
	Contrast	Std. Err.	[95% Conf. Interval]
prog@_predict			
(Yes vs No) 1	.1259899	.0349061	.0575753 .1944045
(Yes vs No) 2	-.0185024	.0054389	-.0291624 -.0078424
(Yes vs No) 3	-.1074874	.0300866	-.1664561 -.0485188

```

. matrix b = r(b)

```

Endogenous treatment model

```

. eoprobit wchange (age over phealth) , ///
>     entreat(prog = age over phealth wtprog ) ///
>     vce(robust) vsquish nolog
Extended ordered probit regression           Number of obs   =       3,000
                                              Wald chi2(6)     =       236.09
Log pseudolikelihood = -4389.0839          Prob > chi2      =       0.0000
    
```

	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
wchange						
prog#c.age						
No	.3318583	.1010243	3.28	0.001	.1338543	.5298624
Yes	.0991993	.0944861	1.05	0.294	-.08599	.2843886
prog#c.over						
No	.4241221	.0527011	8.05	0.000	.3208298	.5274144
Yes	.4310345	.051217	8.42	0.000	.3306509	.5314181
prog# c.phealth						
No	-.3323793	.0665871	-4.99	0.000	-.4628875	-.201871
Yes	-.5973977	.0486921	-12.27	0.000	-.6928325	-.501963
prog						
age	-.9365184	.0828734	-11.30	0.000	-1.098947	-.7740895
over	-1.058259	.0499251	-21.20	0.000	-1.15611	-.9604071
phealth	.8938228	.0498157	17.94	0.000	.7961859	.9914598
wtprog	1.632994	.0760053	21.49	0.000	1.484026	1.781961

	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
wchange						
prog#c.age						
No	.3318583	.1010243	3.28	0.001	.1338543	.5298624
Yes	.0991993	.0944861	1.05	0.294	-.08599	.2843886
prog#c.over						
No	.4241221	.0527011	8.05	0.000	.3208298	.5274144
Yes	.4310345	.051217	8.42	0.000	.3306509	.5314181
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prog						
age	-.9365184	.0828734	-11.30	0.000	-1.098947	-.7740895
over	-1.058259	.0499251	-21.20	0.000	-1.15611	-.9604071
phealth	.8938228	.0498157	17.94	0.000	.7961859	.9914598
wtprog	1.632994	.0760053	21.49	0.000	1.484026	1.781961
_cons	.0130243	.0531604	0.24	0.806	-.0911683	.1172168
/wchange						
prog#c.cut1						
No	-.438465	.0907758			-.6163823	-.2605477
Yes	-.3395413	.0697649			-.4762781	-.2028046
prog#c.cut2						
No	.5647753	.0811816			.4056623	.7238883
Yes	.849572	.0817844			.6892775	1.009867
corr(e.prog, wchange)	-.3419207	.0610844	-5.60	0.000	-.4556747	-.2171783

prog#c.age	No	.3318583	.1010243	3.28	0.001	.1338543	.5298624
	Yes	.0991993	.0944861	1.05	0.294	-.08599	.2843886
prog#c.over	No	.4241221	.0527011	8.05	0.000	.3208298	.5274144
	Yes	.4310345	.051217	8.42	0.000	.3306509	.5314181
prog# c.phealth	No	-.3323793	.0665871	-4.99	0.000	-.4628875	-.201871
	Yes	-.5973977	.0486921	-12.27	0.000	-.6928325	-.501963
prog	age	-.9365184	.0828734	-11.30	0.000	-1.098947	-.7740895
	over	-1.058259	.0499251	-21.20	0.000	-1.15611	-.9604071
	phealth	.8938228	.0498157	17.94	0.000	.7961859	.9914598
	wtprog	1.632994	.0760053	21.49	0.000	1.484026	1.781961
	_cons	.0130243	.0531604	0.24	0.806	-.0911683	.1172168
/wchange	prog#c.cut1						
	No	-.438465	.0907758			-.6163823	-.2605477
	Yes	-.3395413	.0697649			-.4762781	-.2028046
	prog#c.cut2						
	No	.5647753	.0811816			.4056623	.7238883
	Yes	.849572	.0817844			.6892775	1.009867
corr(e.prog, e.wchange)		-.3419207	.0610844	-5.60	0.000	-.4556747	-.2171783

```
. estat teffects
```

```
Predictive margins
```

```
Number of obs      =      3,000
```

```
ATE_Pr0      : Pr(wchange=0=Loss)  
ATE_Pr1      : Pr(wchange=1=No change)  
ATE_Pr2      : Pr(wchange=2=Gain)
```

	Unconditional Margin	Std. Err.	z	P> z	[95% Conf. Interval]	
ATE_Pr0 prog (Yes vs No)	.1087061	.038293	2.84	0.005	.0336531	.1837591
ATE_Pr1 prog (Yes vs No)	.0288781	.0190952	1.51	0.130	-.0085478	.0663039
ATE_Pr2 prog (Yes vs No)	-.1375842	.0322663	-4.26	0.000	-.200825	-.0743433

- When everyone joins the program instead of when no one participants in the program,
 - On average, the probability of “Loss” goes up by .11
 - On average, the probability of “No change” does not change
 - On average, the probability of “Gain” goes down .14

```

. margins r.prog,                               ///
> predict(fix(prog) outlevel("Loss"))         ///
> predict(fix(prog) outlevel("No change"))     ///
> predict(fix(prog) outlevel("Gain"))         ///
> contrast(nowald) vce(unconditional)

```

Contrasts of predictive margins

```

1._predict   : Pr(wchange==Loss), predict(fix(prog) outlevel("Loss"))
2._predict   : Pr(wchange==No change), predict(fix(prog) outlevel("No
change"))
3._predict   : Pr(wchange==Gain), predict(fix(prog) outlevel("Gain"))

```

	Unconditional			
	Contrast	Std. Err.	[95% Conf. Interval]	
prog@_predict				
(Yes vs No) 1	.1087061	.038293	.0336531	.1837591
(Yes vs No) 2	.0288781	.0190952	-.0085478	.0663039
(Yes vs No) 3	-.1375842	.0322663	-.200825	-.0743433

Endogenous sample selection

- Reconsider our fictional weight-loss program
 - Some program participants and some nonparticipants will not show up for the final weigh in
This is commonly known as lost to follow up
 - If unobservables that affect whether someone is lost to follow up
 - are independent of the unobservables that affect program participation
 - and they are independent of the unobservables that affect the outcomes with and without the program,
 - the previously discussed estimator consistently estimates the effects
- Any dependence among the unobservables must be modeled

$$insamp = (\mathbf{x}\alpha + \alpha_1 wtsamp + \xi > 0)$$

$$Pr(wchange == \text{"No change"})$$

$$= \begin{cases} Pr(cut1_0 < \mathbf{x}\beta_0 + \epsilon \leq cut2_0) & \text{if } prog == 0 \\ Pr(cut1_1 < \mathbf{x}\beta_1 + \epsilon \leq cut2_1) & \text{if } prog == 1 \end{cases}$$

(Analogously define probabilities Loss, and Gain)

$$prog = (\mathbf{x}\gamma + \gamma_1 wtprog + \eta > 0)$$

ξ, ϵ and η are joint normal

```
Fit by: eoprobit wchange (age over phealth) ,
        entreat(prog = age over phealth wtprog )
        select(samp = age over phealth wtsamp )
        vce(robust)
```

Data

```
. use wprogram2
```

```
. describe
```

```
Contains data from wprogram2.dta
```

```
  obs:          3,000
```

```
  vars:           8
```

```
  size:         96,000
```

```
28 Jul 2017 07:13
```

variable name	storage type	display format	value label	variable label
wchange	float	%9.0g	changel	Weight change level
age	float	%9.0g		Years over 50
over	float	%9.0g		Overweight (tens of pounds)
phealth	float	%9.0g		Prior health score
prog	float	%9.0g	yesno	Participate in wellness program
wtprog	float	%9.0g	yesno	Offered work time to participate in program
wtsamp	float	%9.0g		Offered work time to participate in sample
insamp	float	%9.0g		In sample: attended initial and final weigh in

```
Sorted by:
```

```

. eoprobit wchange (age over phealth) ,      ///
>       entreat(prog = age over phealth wtprog ) ///
>       select(insamp = age over phealth wtsamp ) ///
>       vce(robust) vsquish nolog

```

```

Extended ordered probit regression           Number of obs   =       3,000
                                             Selected       =       1,884
                                             Nonselected    =       1,116
                                             Wald chi2(6)   =       180.18
                                             Prob > chi2    =       0.0000

Log pseudolikelihood = -4484.2347

```

	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
wchange						
prog#c.age						
No	.3833806	.1306121	2.94	0.003	.1273856	.6393756
Yes	-.0630257	.1084828	-0.58	0.561	-.2756482	.1495967
prog#c.over						
No	.4734046	.0775788	6.10	0.000	.321353	.6254561
Yes	.2110918	.0774768	2.72	0.006	.0592401	.3629436
prog#						
c.phealth						
No	-.3910086	.0839247	-4.66	0.000	-.5554981	-.2265192
Yes	-.8192438	.0675175	-12.13	0.000	-.9515757	-.6869119
insamp						
age	-.0239454	.0805554	-0.30	0.766	-.181831	.1339403
over	-.7639015	.045083	-16.94	0.000	-.8522626	-.6755404
phealth	.7762507	.0467149	16.62	0.000	.6846911	.8678104
wtsamp	2.614852	.2666563	9.81	0.000	2.092215	3.137489
cons	.2834801	.0516434	5.49	0.000	.1822608	.3846994

c.phealth							
No		-.3910086	.0839247	-4.66	0.000	-.5554981	-.2265192
Yes		-.8192438	.0675175	-12.13	0.000	-.9515757	-.6869119
insamp							
age		-.0239454	.0805554	-0.30	0.766	-.181831	.1339403
over		-.7639015	.045083	-16.94	0.000	-.8522626	-.6755404
phealth		.7762507	.0467149	16.62	0.000	.6846911	.8678104
wtsamp		2.614852	.2666563	9.81	0.000	2.092215	3.137489
_cons		.2834801	.0516434	5.49	0.000	.1822608	.3846994
prog							
age		-.9366997	.0818766	-11.44	0.000	-1.097175	-.7762245
over		-1.062399	.0491499	-21.62	0.000	-1.158731	-.9660671
phealth		.8913551	.0494733	18.02	0.000	.7943892	.988321
wtprog		1.645957	.0729847	22.55	0.000	1.502909	1.789004
_cons		.016411	.0527191	0.31	0.756	-.0869166	.1197386
/wchange							
prog#c.cut1							
No		-.3561706	.1278314			-.6067155	-.1056258
Yes		-.4668053	.0986098			-.660077	-.2735335
prog#c.cut2							
No		.6304983	.1309562			.3738289	.8871677
Yes		.721275	.1430156			.4409696	1.00158
corr(e.insamp,							
e.wchange)		-.5691458	.0901455	-6.31	0.000	-.7199754	-.366975
corr(e.prog,							
e.wchange)		-.5310186	.0707529	-7.51	0.000	-.6553935	-.3786047
corr(e.prog,							
e.insamp)		.4757458	.0296034	16.07	0.000	.4156943	.5316674

	1.748337	1.0723317	22.88	0.000	1.882333	1.748337
_cons	.016411	.0527191	0.31	0.756	-.0869166	.1197386
/wchange						
prog#c.cut1						
No	-.3561706	.1278314			-.6067155	-.1056258
Yes	-.4668053	.0986098			-.660077	-.2735335
prog#c.cut2						
No	.6304983	.1309562			.3738289	.8871677
Yes	.721275	.1430156			.4409696	1.00158
corr(e.insamp,						
e.wchange)	-.5691458	.0901455	-6.31	0.000	-.7199754	-.366975
corr(e.prog,						
e.wchange)	-.5310186	.0707529	-7.51	0.000	-.6553935	-.3786047
corr(e.prog,						
e.insamp)	.4757458	.0296034	16.07	0.000	.4156943	.5316674

- Nonzero correlation between `e.insamp` and `e.wchange` implies endogenous sample selection for outcomes
- Nonzero correlation between `e.prog` and `e.wchange` implies endogenous treatment assignment

```
. estat teffects
```

```
Predictive margins
```

```
Number of obs      =      3,000
```

```
ATE_Pr0      : Pr(wchange=0=Loss)  
ATE_Pr1      : Pr(wchange=1=No change)  
ATE_Pr2      : Pr(wchange=2=Gain)
```

	Unconditional Margin	Std. Err.	z	P> z	[95% Conf. Interval]	
ATE_Pr0 prog (Yes vs No)	.1552606	.051808	3.00	0.003	.0537189	.2568024
ATE_Pr1 prog (Yes vs No)	.006893	.0300435	0.23	0.819	-.0519913	.0657772
ATE_Pr2 prog (Yes vs No)	-.1621536	.038066	-4.26	0.000	-.2367616	-.0875457

- When everyone joins the program instead of when no one participants in the program,
 - On average, the probability of “Loss” goes up
 - On average, the probability of “No change” does not change
 - On average, the probability of “Gain” goes down

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