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**Problem Set 3 *Solutions***

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**Question 1.** Return to the NELS-88 data used in Problem Set 2 to estimate the academic benefits to attending a Catholic high school. This time—rather than exact or nearest neighbor matching based on covariates—we will use propensity scores. **(30 points)**

- (a) For this analysis, use the “continuous” family income variable you created in Problem Set 2 and the dummy variables for parents’ highest level of education. In addition, create *z*-scores for the 8th and 12th grade reading and math scores. **(3 points)**

**See the attached log file for creation of additional variables.**

- (b) Use `teffects psmatch` or the `psmatch2` commands to estimate a propensity score model where the “treatment” is attending a Catholic high school. The goal will ultimately be (in part c) to estimate the ATT on 12th grade test scores, high school graduation, and post-secondary enrollment, using nearest neighbor matching (based on propensity scores). This will be an iterative process where you experiment with a propensity score model, check for balance, and then make adjustments to your propensity score model and matching rules as needed. I recommend using the `quietly` prefix with `teffects psmatch`, or omitting the `outcome()` option if you use the `psmatch2` command. (You do not want treatment effect estimates to guide your specification search). Here are a few tips/requirements: **(12 points)**
- Choose predictor variables that are likely to be associated with the “treatment” that you would ultimately like to see balanced between your treated and untreated group. You can use any variables in the dataset that you deem appropriate.
  - After fitting the propensity score model, check for balance on your predictor variables using `tebalance summarize`, `box` and `density`. (Or use `pstest` after `psmatch2`).
  - You may be able to improve balance by changing your propensity model specification—e.g., omitting or including variables (depending on how predictive or theoretically important they are), entering variables as continuous or categorical, adding interactions or nonlinear terms (e.g., quadratic)—and/or by tinkering with the number of nearest neighbors or caliper. Use your own judgment when deciding on “good enough” balance.
  - You do not need to provide results for all of the iterations you attempt. Just include a short written explanation justifying your choice, and provide balance tests/figures for your final specification. (You can refer to other specifications you tried in your write-up).

- Lastly, once you have settled on a propensity score model, check for overlap in the distribution of propensity scores between your treated and untreated group. (E.g., `teoverlap` or `tebalance density` after `teffects psmatch`, or using code provided in class). Include your graphical results with your output. Presuming you have good overlap, you can proceed to the next step. If there is poor overlap, you should revisit your propensity score model.

My final model is shown in the attached log (yours will likely differ). Of the confounders, I prioritized balance on baseline test scores, family income, and parental education, given the results of prior studies which demonstrate the importance of these in explaining later outcomes. The logit model results confirm these are important predictors of Catholic school enrollment as well. I experimented with several different specifications and variable definitions; these included models linear in prior test scores, models that used separate categorical variables for the highest education of each parent, models with interactions between gender and race, and models with a continuous measure of risk factors. The covariate balance was quite good for most specifications, but this one seemed especially good, as the balance test results show. (The log file shows the `tebalance summarize` for the same propensity score match and the `tebalance box` and `tebalance density` for select variables).

The `teoverlap` and `tebalance density` plots are also shown in the attached. Note that the former uses `*all*` observations, not just the matched sample. The latter shows both the full and matched sample.

- (c) Once you are satisfied with your propensity score model, calculate the ATT for the four outcome variables: 12th grade reading and math *z*-scores, high school graduation, and post-secondary enrollment. Interpret the results in words. What assumption(s) are required for these estimates to be considered causal? (5 points)

The results are shown in the attached log and summarized in the table below. Attending a Catholic high school is estimated to have a 0.098 standard deviation effect on math scores and a -0.028 standard deviation effect on reading scores. Only the math effect is statistically significant. The ATT estimate is positive and marginally insignificant for high school graduation (1.7 percentage points) and positive and significant for post-secondary enrollment (6.8 ppts). Because these are ATT estimates they are interpreted as the average treatment effect for the population who attends Catholic high school. The key assumption is conditional independence—conditional on the covariates (here, factors used to create balance between the treated and untreated cases), treatment assignment is independent of potential outcomes.

- (d) Rather than nearest neighbor matching, propensity scores can also be used in weighting estimators. Using the same propensity score model you settled on in part (b), estimate the ATT and ATE using inverse probability weighting (`teffects ipw`). How do your results differ from those in part (c), if at all? **(5 points)**

**The results are shown in the attached log and summarized in the table below. The ATT results are similar to those using propensity score matching, though most effects are a little smaller. One exception is high school graduation, with an effect that is a bit larger and statistically significant.**

- (e) Imbens (2015) proposed an algorithm for estimating propensity score models. The algorithm iteratively adds linear and quadratic terms (and interactions), keeping terms that improve the predictive fit of the model. The user-written command `pselect` executes this algorithm and outputs the resulting propensity scores to your dataset. (You will need to install it using `ssc install pselect`). The syntax of the command is:

```
pselect treat, totry(varnames) genpscore(newvarname)
```

where *treat* is the treatment variable, *varnames* is a list of predictor variables you would like to try in the algorithm, and *newvarname* will be the new variable containing the propensity score. Choose a set of variables for the algorithm to try. (Note if you choose a long list it may take quite awhile for the algorithm to run. If it takes an exceedingly long time, start with a shorter list). What specification did the algorithm end up with? **(5 points)**

Note: the resulting propensity scores from part (e) could then be used for matching, stratification, or weighting.

**The resulting model specification is shown in the attached log. I had the algorithm try the same set of variables used in the earlier steps. The resulting specification included some nonlinear terms (e.g., a quadratic in prior math scores) and many interactions (e.g., Black and family income). See the log for an example of how to use the resulting model specification in a `teffects` command.**

```

.
. // *****
. //
. // Regression II - Problem set 3
. // Last updated: September 19, 2025
. //
. // *****
.
. // *****
. // Question 1
. // *****
.
. use https://stats.idre.ucla.edu/stat/stata/examples/methods_matter/chapter12/catholic, c
> lear

```

```

.
. // *****
. // Part a - create some new vars
. // as in Problem Set 2. Also create
. // z-scores for tests
. // *****
.
.      *ssc install fre
.      fre faminc8

```

faminc8 -- total annual family income in 8th grade

		Freq.	Percent	Valid	Cum.
Valid	1 none	18	0.32	0.32	0.32
	2 <\$1000	42	0.74	0.74	1.06
	3 \$1000-\$2999	84	1.48	1.48	2.54
	4 \$3000-\$4999	85	1.50	1.50	4.04
	5 \$5000-\$7499	144	2.54	2.54	6.58
	6 7500-\$9999	175	3.09	3.09	9.66
	7 \$10000-\$14999	447	7.88	7.88	17.55
	8 \$15000-\$19999	441	7.78	7.78	25.32
	9 \$20000-\$24999	655	11.55	11.55	36.87
	10 \$25000-\$34999	1267	22.34	22.34	59.21
	11 35000-\$49999	1419	25.02	25.02	84.24
	12 50000-\$74999	894	15.76	15.76	100.00
	Total	5671	100.00	100.00	

```

.
.      // "continuous" version of family income
.      gen faminc8b=0 if faminc8==1
(5,653 missing values generated)
.
.      replace faminc8b = (0+1000)/2 if faminc8==2
(42 real changes made)
.
.      replace faminc8b = (1000+2999)/2 if faminc8==3
(84 real changes made)
.
.      replace faminc8b = (3000+4999)/2 if faminc8==4
(85 real changes made)
.
.      replace faminc8b = (5000+7499)/2 if faminc8==5
(144 real changes made)
.
.      replace faminc8b = (7500+9999)/2 if faminc8==6
(175 real changes made)
.
.      replace faminc8b = (10000+14999)/2 if faminc8==7
(447 real changes made)

```

```

.      replace faminc8b = (15000+19999)/2 if faminc8==8
(441 real changes made)

.      replace faminc8b = (20000+24999)/2 if faminc8==9
(655 real changes made)

.      replace faminc8b = (25000+34999)/2 if faminc8==10
(1,267 real changes made)

.      replace faminc8b = (35000+49999)/2 if faminc8==11
(1,419 real changes made)

.      replace faminc8b = (50000+74999)/2 if faminc8==12
(894 real changes made)

.      label var faminc8b "family income in 8th grade (dollars)"

.
.      // 3-category version of family income (following Murnane and Willett)
.      gen faminc8c = 1 if faminc8<=8
(4,235 missing values generated)

.      replace faminc8c = 2 if faminc8>=9 & faminc8<=10
(1,922 real changes made)

.      replace faminc8c = 3 if faminc8>=11 & faminc8~=.
(2,313 real changes made)

.      label var faminc8c "family income in 8th grade (three categories)"

.
.      // 4-category version of 8th grade math scores
.      egen math8b=cut(math8), at(30,38,44,51,80) icodes

.      replace math8b=math8b+1
(5,671 real changes made)

.      label var math8b "8th grade math score (four categories)"

.
.      // father's highest education
.      // NOTE: code 8 is "don't know". Below set vars to missing in this case
.      codebook fathed8

-----
fathed8                                     father^s highest level of education
-----

      Type: Numeric (byte)
      Label: farcat

      Range: [1,8]                               Units: 1
Unique values: 8                               Missing .: 0/5,671

      Tabulation: Freq.   Numeric   Label
                   873         1   not finish hs
                   1,778       2   hs grad
                   660         3   junior coll
                   443         4   coll <4
                   743         5   coll grad
                   346         6   masters
                   141         7   doctorate
                   687         8   dont know

.      gen fathed1 = fathed8==1 /* hs dropout */
.      gen fathed2 = fathed8==2 /* hs grad */

```

```

.       gen fathed3 = (fathed8>=3 & fathed8<=4) /* some college */
.       gen fathed4 = (fathed8>=5 & fathed8<=7) /* 4yr college or more */
.       label var fathed1 "father's highest ed: hs dropout"
.       label var fathed2 "father's highest ed: hs grad"
.       label var fathed3 "father's highest ed: some college"
.       label var fathed4 "father's highest ed: 4yr college or more"
.
.       // mother's highest education
.       // NOTE: code 8 is "don't know". Below set vars to missing in this case
.       codebook mothed8
-----
mothed8                                     mother^s highest level of education
-----
Type: Numeric (byte)
Label: farcat

Range: [1,8]                               Units: 1
Unique values: 8                           Missing .: 0/5,671

Tabulation: Freq.    Numeric    Label
             815         1    not finish hs
             2,091        2    hs grad
             686         3    junior coll
             468         4    coll <4
             655         5    coll grad
             299         6    masters
             82          7    doctorate
             575         8    dont know

.       gen mothed1 = mothed8==1 /* hs dropout */
.       gen mothed2 = mothed8==2 /* hs grad */
.       gen mothed3 = (mothed8>=3 & mothed8<=4) /* some college */
.       gen mothed4 = (mothed8>=5 & mothed8<=7) /* 4yr college or more */
.       label var mothed1 "mother's highest ed: hs dropout"
.       label var mothed2 "mother's highest ed: hs grad"
.       label var mothed3 "mother's highest ed: some college"
.       label var mothed4 "mother's highest ed: 4yr college or more"
.
.       forvalues j=1/4 {
2.         replace fathed`j'=. if fathed8==. | fathed8==8
3.         replace mothed`j'=. if mothed8==. | mothed8==8
4.       }
(687 real changes made, 687 to missing)
(575 real changes made, 575 to missing)
(687 real changes made, 687 to missing)
(575 real changes made, 575 to missing)
(687 real changes made, 687 to missing)
(575 real changes made, 575 to missing)
(687 real changes made, 687 to missing)
(575 real changes made, 575 to missing)
.

```

```

.      // highest education of two parents
.      // NOTE: code 8 is "don't know" so remove these first before taking max
.      gen ftemp = fathed8 if fathed8~=8
(687 missing values generated)

.      gen mtemp = mothed8 if mothed8~=8
(575 missing values generated)

.      egen pared8=rowmax(ftemp mtemp)
(406 missing values generated)

.      gen pared1 = pared8==1 /* hs dropout */
.      gen pared2 = pared8==2 /* hs grad */
.      gen pared3 = (pared8>=3 & pared8<=4) /* some college */
.      gen pared4 = (pared8>=5 & pared8<=7) /* 4yr college or more */
.      label var pared1 "parent's highest ed: hs dropout"
.      label var pared2 "parent's highest ed: hs grad"
.      label var pared3 "parent's highest ed: some college"
.      label var pared4 "parent's highest ed: 4yr college or more"
.      label var pared8 "parent's highest education"
.      drop ftemp mtemp

.
.      // z-scores for 8th and 12th grade reading and math scores
.      foreach g in 8 12 {
2.          foreach s in read math {
3.              egen `s'`g'z = std(`s'`g')
4.              label var `s'`g'z "z-score for `g'th grade `s'"
5.              }
6.          }

.
.      // parent expects child to go to college
.      codebook fhowfar mhowfar
-----
fhowfar                                     how far in schl r^s father wants r to go
-----

      Type: Numeric (byte)
      Label: farcat2

      Range: [1,6]                               Units: 1
Unique values: 6                               Missing .: 0/5,671

      Tabulation: Freq.    Numeric    Label
                   47         1    not finish hs
                   309        2     hs grad
                   384        3   junior coll
                   595        4    coll <4
                  2,889        5    coll grad
                  1,447        6   postsec ed
-----
mhowfar                                     how far in schl r^s mother wants r to go
-----

      Type: Numeric (byte)
      Label: farcat2

      Range: [1,6]                               Units: 1
Unique values: 6                               Missing .: 0/5,671

      Tabulation: Freq.    Numeric    Label
                   42         1    not finish hs
                   275        2     hs grad
                   361        3   junior coll
                   577        4    coll <4
                  2,928        5    coll grad
                  1,488        6   postsec ed

```





```
.      tebalance summarize math8z read8z female black hisp api nativam ///
>      riskdrop1 riskdrop2 disrupt nohw8 faminc8b pared1-pared4 ///
>      parmarried collegexp
```

Covariate balance summary

	Raw	Matched
Number of obs =	5,671	1,184
Treated obs =	592	592
Control obs =	5,079	592

	Standardized differences		Variance ratio	
	Raw	Matched	Raw	Matched
math8z	.2606656	-.0495814	.8200688	1.023323
read8z	.4356571	-.04546	.9223486	1.051909
female	.0496905	.0135434	.9955598	.9978893
black	-.1579425	.0219152	.6082682	1.087891
hisp	-.0974819	.030214	.7768816	1.094018
api	-.1926191	.0895978	.3939964	1.976068
nativam	-.0940456	-.0786986	.5998088	.6452951
riskdrop1	-.0974069	-.0041294	.8844729	.9941924
riskdrop2	-.4043775	-.045471	.3184886	.8323846
disrupt8	-.0513382	0	.9158064	1
nohw8	-.2800718	-.0330567	.4771307	.8944509
faminc8b	.4572743	.0162643	.8885848	.9480218
pared1	-.3104968	.021481	.2860831	1.138903
pared2	-.1167283	-.1011173	.8976232	.9077325
pared3	.0275791	.0473309	1.034677	1.058908
pared4	.2866933	.0172299	1.224495	1.007103
parmarried	.2616919	.051715	.5542313	.8669075
collegexp	.2563305	-.0160351	.6169925	1.040199

```
.      // BONUS: plotting the standardized differences (raw/matched)
.      mat      balance = r(table)

.      coefplot (matrix(balance[,1])) (matrix(balance[,2])), ///
>      xline(0,lpattern(solid)) xline(-0.05 0.05,lcolor(red)) ///
>      xlab(-0.45(0.05)0.45) xtitle("Standardized difference") ///
>      legend(order(2 "Raw" 4 "Matched") position(6) rows(1)) ///
>      sort(1) graphregion(margin(1+5)) title("Standardized differences: raw an
> d matched") ///
>      xsize(10) ysize(4) name(graph1,replace)
(balance: could not determine CI1)
(balance: could not determine CI1)
```

```
.      graph export graph1.pdf, as(pdf) replace
file graph1.pdf saved as PDF format
```

```
.      // graphically compare distributions for continuous variables
.      tebalance box math8z, name(balmath, replace)

.      tebalance box read8z, name(balread, replace)

.      tebalance density faminc8b, name(balinc, replace)

.      graph combine balmath balread balinc, col(1) xsize(4) ysize(8) ///
>      name(graph2, replace) ///
>      title(Covariate balance: after teffects psmatch, size(medsmall))
```

```
.      graph export graph2.pdf, as(pdf) replace
file graph2.pdf saved as PDF format
```

```

.
. // graphically compare distributions for propensity scores
. // (all observations + matched sample only)
. tebalance density, name(graph3, replace) ///
> byopts(title(Propensity score distribution: all observations and matched
> sample, size(medsmall))) ///
> legend(order(1 "Untreated" 2 "Treated") position(6))

.
. // graphically compare distributions of propensity scores (all observations
. // using teoverlap)
. teoverlap, ptlevel(1) name(graph4, replace) ///
> title(Propensity score distribution: all observations using teoverlap, size(m
> edsmall))

.
. graph combine graph3 graph4, col(1) xsize(6) ysize(8) ///
> name(graph5, replace)

. graph export overlap.pdf, as(pdf) replace
file overlap.pdf saved as PDF format

. graph close _all

.
. // FYI to see actual logit results--which variables are significant
. // predictors of treatment? How strong of a relationship?
. logit catholic c.math8z##c.math8z ///
> c.read8z##c.read8z female black hisp api nativam riskdrop1 ///
> riskdrop2 disrupt nohw8 c.faminc8b##c.faminc8b pared1-pared4 ///
> parmarried collegexp

```

```

Iteration 0: Log likelihood = -1897.6568
Iteration 1: Log likelihood = -1779.3796
Iteration 2: Log likelihood = -1763.2706
Iteration 3: Log likelihood = -1763.0145
Iteration 4: Log likelihood = -1763.0138
Iteration 5: Log likelihood = -1763.0138

```

Logistic regression

```

Number of obs = 5,671
LR chi2(20) = 269.29
Prob > chi2 = 0.0000
Pseudo R2 = 0.0710

```

Log likelihood = -1763.0138

	catholic	Coefficient	Std. err.	z	P> z	[95% conf. interval]	
	math8z	-.0630993	.0732242	-0.86	0.389	-.2066161	.0804176
	c.math8z#c.math8z	-.1692552	.0495166	-3.42	0.001	-.2663059	-.0722044
	read8z	.3217844	.067893	4.74	0.000	.1887166	.4548523
	c.read8z#c.read8z	.0104647	.0484315	0.22	0.829	-.0844593	.1053886
	female	.0409147	.095074	0.43	0.667	-.1454269	.2272564
	black	-.2491715	.1918147	-1.30	0.194	-.6251214	.1267785
	hisp	-.0945902	.1588538	-0.60	0.552	-.405938	.2167576
	api	-1.176192	.2813161	-4.18	0.000	-1.727561	-.6248225
	nativam	-.4881439	.2865059	-1.70	0.088	-1.049685	.0733975
	riskdrop1	.0250028	.1227969	0.20	0.839	-.2156748	.2656803
	riskdrop2	-.4032556	.2596487	-1.55	0.120	-.9121577	.1056465
	disrupt8	.2221792	.1285998	1.73	0.084	-.0298717	.4742302
	nohw8	-.6271156	.1773633	-3.54	0.000	-.9747412	-.27949
	faminc8b	.0000294	.0000145	2.03	0.042	1.07e-06	.0000578
	c.faminc8b#c.faminc8b	-2.06e-10	1.73e-10	-1.19	0.234	-5.46e-10	1.33e-10
	pared1	-.6229521	.3245582	-1.92	0.055	-1.259075	.0131703
	pared2	.0491702	.2057076	0.24	0.811	-.3540093	.4523496
	pared3	.1288713	.2068516	0.62	0.533	-.2765504	.534293
	pared4	.3233567	.2025939	1.60	0.110	-.0737201	.7204335
	parmarried	.2604802	.1804001	1.44	0.149	-.0930976	.6140579
	collegexp	.2769345	.1431216	1.93	0.053	-.0035785	.5574476
	_cons	-3.23417	.4041378	-8.00	0.000	-4.026266	-2.442075

```
.
. // FYI to see logit results in terms of change in predicted probability
. // of treatment (not logit coefficients)
. margins, dydx(*) atmeans
```

Conditional marginal effects  
Model VCE: OIM

Number of obs = 5,671

```
Expression: Pr(catholic), predict()
dy/dx wrt: math8z read8z female black hisp api nativam riskdrop1 riskdrop2 disrupt8
           nohw8 faminc8b pared1 pared2 pared3 pared4 parmarried collegexp
At: math8z   = 3.91e-10 (mean)
    read8z   = -1.01e-09 (mean)
    female   = .5200141 (mean)
    black    = .0975137 (mean)
    hisp     = .1162053 (mean)
    api      = .0585435 (mean)
    nativam  = .0384412 (mean)
    riskdrop1 = .2479281 (mean)
    riskdrop2 = .1579968 (mean)
    disrupt8 = .1795098 (mean)
    nohw8    = .143361 (mean)
    faminc8b = 32656.05 (mean)
    pared1   = .0946923 (mean)
    pared2   = .3091166 (mean)
    pared3   = .241051 (mean)
    pared4   = .2835479 (mean)
    parmarried = .8335391 (mean)
    collegexp = .8012696 (mean)
```

	dy/dx	Delta-method std. err.	z	P> z	[95% conf. interval]	
math8z	-.0057371	.0065909	-0.87	0.384	-.018655	.0071808
read8z	.0292574	.0065043	4.50	0.000	.0165092	.0420056
female	.0037201	.0086508	0.43	0.667	-.0132351	.0206752
black	-.0226553	.0173323	-1.31	0.191	-.0566259	.0113154
hisp	-.0086004	.0144423	-0.60	0.552	-.0369068	.0197061
api	-.1069421	.0256707	-4.17	0.000	-.1572558	-.0566285
nativam	-.0443832	.0261398	-1.70	0.090	-.0956163	.00685
riskdrop1	.0022733	.0111812	0.20	0.839	-.0196414	.0241881
riskdrop2	-.0366649	.0229526	-1.60	0.110	-.0816513	.0083214
disrupt8	.0202011	.0117769	1.72	0.086	-.0028812	.0432833
nohw8	-.0570188	.0160873	-3.54	0.000	-.0885494	-.0254883
faminc8b	1.45e-06	4.24e-07	3.42	0.001	6.19e-07	2.28e-06
pared1	-.0566403	.0294206	-1.93	0.054	-.1143036	.0010231
pared2	.0044707	.018696	0.24	0.811	-.0321728	.0411142
pared3	.0117173	.0187864	0.62	0.533	-.0251034	.0485379
pared4	.0294003	.0184974	1.59	0.112	-.0068538	.0656545
parmarried	.0236835	.0164338	1.44	0.150	-.0085262	.0558931
collegexp	.0251795	.0129571	1.94	0.052	-.000216	.050575

```
.
. // BONUS: while it is very easy to see balance expressed as standardized
. // differences (using tebalance summarize) it is less obvious how to get a
. // balance table in the original units. teffects doesn't tag the matched
. // observations in the same way psmatch2 does, so you have to manually ID
. // the matches. There may be other ways to do it, but the below works.
.
. capture drop ob
.
. gen ob=_n
.
. preserve
.
. tempfile treated
```

```
.      keep if catholic==1
(5,079 observations deleted)

.      keep nn1

.      bysort nn1: gen weight=_N

.      by nn1: keep if _n==1
(63 observations deleted)

.      rename nn1 ob

.      save `treated'
file C:\Users\corcorosp\AppData\Local\Temp\ST_3d28_000002.tmp saved as .dta format

.      restore

.      merge m:1 ob using `treated'
(variable ob was float, now double to accommodate using data's values)
```

Result	Number of obs	
Not matched	5,142	
from master	5,142	(_merge==1)
from using	0	(_merge==2)
Matched	529	(_merge==3)

```
.      replace weight=1 if catholic==1
(592 real changes made)

.      // this new "weight" variable is equal to 1 for all treated cases and
.      // equal to an integer value 1+ for MATCHED untreated cases (it is >1 if
.      // the observation was matched more than once). You can now condition
.      // (and use fweights) using this weight variable.
.
.      // balance table using new dtable command (with p-values)
.      // use the below for labeling purposes
.      gen catholic2=catholic

.      label define catholic2 0 "Matched untreated" 1 "Treated"

.      label values catholic2 catholic2

.      label var catholic2 "Attended Catholic HS"

.
.      dtable math8z read8z faminc8b female black hisp api nativam riskdrop1 ///
>      riskdrop2 disrupt nohw8 pared1 pared2 pared3 pared4 parmarried ///
>      collegexp if weight~= . [fweight=weight], ///
>      by(catholic2, nototal tests) nosample col(test(pvalue)) ///
>      cont(,stat(mean))
note: using test regress across levels of catholic2 for math8z, read8z, faminc8b,
female, black, hisp, api, nativam, riskdrop1, riskdrop2, disrupt8, nohw8, pared1,
pared2, pared3, pared4, parmarried, and collegexp.
```

	Attended Catholic HS		
	Matched untreated	Treated	pvalue
z-score for 8th grade math	0.269	0.224	0.394
z-score for 8th grade read	0.424	0.381	0.434
family income in 8th grade (dollars)	39,265.549	39,534.130	0.780
student is female?	0.535	0.542	0.816
student is black?	0.054	0.059	0.706
student is hispanic?	0.081	0.090	0.603
student is asian/pacific islander?	0.012	0.024	0.123
student is native american?	0.037	0.024	0.176
=1 if 1 dropout risk factor	0.213	0.211	0.943
=1 if 2-5 dropout risk factors	0.057	0.047	0.434
student frequently disruptive	0.162	0.162	1.000
student rarely completes homework	0.074	0.066	0.570
parent's highest ed: hs dropout	0.024	0.027	0.712
parent's highest ed: hs grad	0.307	0.262	0.082
parent's highest ed: some college	0.231	0.252	0.416
parent's highest ed: 4yr college or more	0.395	0.404	0.767
=1 if parents married in 8th grade	0.897	0.912	0.374
=1 if mother or father expects college+	0.890	0.885	0.783

```

.
.      drop nn1 nn2 ob weight _merge catholic2
.
.
. // *****
. // Part c - estimate ATT using model
. // specification chosen above
. // *****
.
.      foreach j in math12z read12z hsgrad inpse {
2.          display in red "Outcome: `j'"
3.
.          _eststo psm`j': teffects psmatch (`j') (catholic ///
>          c.math8z##c.math8z c.read8z##c.read8z female black ///
>          hisp api nativam riskdrop1 riskdrop2 disrupt nohw8 ///
>          c.faminc8b##c.faminc8b pared1-pared4 ///
>          parmarrried collegexp, logit), atet
4.      }
Outcome: math12z

Treatment-effects estimation      Number of obs      =      5,671
Estimator      : propensity-score matching      Matches: requested =      1
Outcome model  : matching      min =      1
Treatment model: logit      max =      2
-----
      math12z |      Coefficient      AI robust
      |      std. err.      z      P>|z|      [95% conf. interval]
-----+-----
ATET
catholic |
(yes vs no) |      .0976228      .0389805      2.50      0.012      .0212223      .1740232
-----+-----
Outcome: read12z

Treatment-effects estimation      Number of obs      =      5,671
Estimator      : propensity-score matching      Matches: requested =      1
Outcome model  : matching      min =      1
Treatment model: logit      max =      2
-----
      read12z |      Coefficient      AI robust
      |      std. err.      z      P>|z|      [95% conf. interval]
-----+-----
ATET
catholic |
(yes vs no) |      -.0279133      .0394335      -0.71      0.479      -.1052015      .0493749
-----+-----
Outcome: hsgrad

Treatment-effects estimation      Number of obs      =      5,671
Estimator      : propensity-score matching      Matches: requested =      1
Outcome model  : matching      min =      1
Treatment model: logit      max =      2
-----
      hsgrad |      Coefficient      AI robust
      |      std. err.      z      P>|z|      [95% conf. interval]
-----+-----
ATET
catholic |
(yes vs no) |      .0168919      .0108328      1.56      0.119      -.00434      .0381238
-----+-----
Outcome: inpse

Treatment-effects estimation      Number of obs      =      5,671
Estimator      : propensity-score matching      Matches: requested =      1
Outcome model  : matching      min =      1
Treatment model: logit      max =      2
-----
      inpse |      Coefficient      AI robust
      |      std. err.      z      P>|z|      [95% conf. interval]
-----+-----
ATET
catholic |
(yes vs no) |      .0675676      .0208701      3.24      0.001      .0266628      .1084723
-----+-----

```

```

.
.
. // *****
. // Part d - estimate ATT and ATE using IPW and
. // pscore model decided above
. // *****
.
.   foreach j in math12z read12z hsgrad inpse {
2.       display in red "Outcome: `j'"
3.
.       _eststo ipwatt`j': teffects ipw (`j') (catholic ///
>         c.math8z##c.math8z c.read8z##c.read8z female black ///
>         hisp api nativam riskdrop1 riskdrop2 disrupt nohw8 ///
>         c.faminc8b##c.faminc8b pared1-pared4 ///
>         parmarried collegexp, logit), atet
4.
.       _eststo ipwate`j': teffects ipw (`j') (catholic ///
>         c.math8z##c.math8z c.read8z##c.read8z female black ///
>         hisp api nativam riskdrop1 riskdrop2 disrupt nohw8 ///
>         c.faminc8b##c.faminc8b pared1-pared4 ///
>         parmarried collegexp, logit), ate
5.   }
Outcome: math12z

Iteration 0:  EE criterion = 5.352e-23
Iteration 1:  EE criterion = 4.373e-33
The Gauss-Newton stopping criterion has been met but missing standard errors
indicate some of the parameters are not identified.

```

```

Treatment-effects estimation      Number of obs      =      5,671
Estimator      : inverse-probability weights
Outcome model   : weighted mean
Treatment model: logit

```

	math12z	Coefficient	Robust std. err.	z	P> z	[95% conf. interval]	
ATET	catholic (yes vs no)	.1188871	.0230871	5.15	0.000	.0736373	.1641369
POMean	catholic no	.2482061	.0318171	7.80	0.000	.1858458	.3105664

Warning: Convergence not achieved.

```

Iteration 0:  EE criterion = 5.352e-23
Iteration 1:  EE criterion = 6.474e-32
The Gauss-Newton stopping criterion has been met but missing standard errors
indicate some of the parameters are not identified.

```

```

Treatment-effects estimation      Number of obs      =      5,671
Estimator      : inverse-probability weights
Outcome model   : weighted mean
Treatment model: logit

```

	math12z	Coefficient	Robust std. err.	z	P> z	[95% conf. interval]	
ATE	catholic (yes vs no)	.1095981	.0527149	2.08	0.038	.0062788	.2129174
POMean	catholic no	-.0124144	.0134565	-0.92	0.356	-.0387886	.0139599

Warning: Convergence not achieved.

Outcome: read12z

```

Iteration 0:  EE criterion = 5.352e-23
Iteration 1:  EE criterion = 1.143e-32
The Gauss-Newton stopping criterion has been met but missing standard errors
indicate some of the parameters are not identified.

```

Treatment model: logit

POMean							
	catholic						
	no	.2883356	.0292549	9.86	0.000	.2309969	.3456742

Warning: Convergence not achieved.

Iteration 0: EE criterion = 5.352e-23

Iteration 1: EE criterion = 7.017e-32

The Gauss-Newton stopping criterion has been met but missing standard errors indicate some of the parameters are not identified.

Treatment model: logit

P0mean							
	catholic						
	no	-.0041737	.013563	-0.31	0.758	-.0307568	.0224093

Warning: Convergence not achieved.

Outcome: hsgrad

Iteration 0: EE criterion = 5.352e-23

Iteration 1: EE criterion = 2.555e-32

The Gauss-Newton stopping criterion has been met but missing standard errors indicate some of the parameters are not identified.

Treatment model: logit

POMean							
	catholic						
	no	.9525385	.0038179	249.49	0.000	.9450556	.9600214

Warning: Convergence not achieved.

```
Iteration 0:  EE criterion = 5.352e-23
```

```
Iteration 1:  EE criterion = 1.472e-32
```

The Gauss-Newton stopping criterion has been met but missing standard errors indicate some of the parameters are not identified.

Treatment-effects estimation	Number of obs	=	5,671
Estimator	: inverse-probability weights		
Outcome model	: weighted mean		
Treatment model	: logit		

	hsgrad	Coefficient	Robust std. err.	z	P> z	[95% conf. interval]	
ATE							
	catholic (yes vs no)	.0307212	.0196568	1.56	0.118	-.0078054	.0692477
POmean							
	catholic no	.9146358	.0038232	239.23	0.000	.9071425	.9221292

```
Warning: Convergence not achieved.
Outcome: inpse
```

```
Iteration 0:  EE criterion = 5.352e-23
Iteration 1:  EE criterion = 3.517e-33
The Gauss-Newton stopping criterion has been met but missing standard errors
indicate some of the parameters are not identified.
```

Treatment-effects estimation	Number of obs	=	5,671
Estimator	: inverse-probability weights		
Outcome model	: weighted mean		
Treatment model	: logit		

inps		Coefficient	Robust std. err.	z	P> z	[95% conf. interval]	
ATET							
	catholic (yes vs no)	.0620777	.0148643	4.18	0.000	.0329441	.0912112
POmean							
	catholic no	.7994088	.0089341	89.48	0.000	.7818984	.8169193

Warning: Convergence not achieved.

```
Iteration 0:  EE criterion = 5.352e-23
Iteration 1:  EE criterion = 1.188e-32
The Gauss-Newton stopping criterion has been met but missing standard errors
indicate some of the parameters are not identified.
```

Treatment-effects estimation	Number of obs	=	5,671
Estimator	: inverse-probability weights		
Outcome model	: weighted mean		
Treatment model	: logit		

	inps	Coefficient	Robust std. err.	z	P> z	[95% conf. interval]	
ATE							
	catholic (yes vs no)	.1274161	.0201821	6.31	0.000	.0878599	.1669723
POmean							
	catholic no	.7027407	.006283	111.85	0.000	.6904263	.715055

Warning: Convergence not achieved.

```
.      esttab _all using PS3estimates.csv, se paren csv replace
(output written to PS3estimates.csv)
```





```

. // OR, you can take the model specification that results from pselect
. // and put it into your teffects command:
. foreach j in math12z read12z hsgrad inpse {
2.     display in red "Outcome: `j'"
3.     teffects psmatch (`j') (catholic $fullmodel, logit), atet
4. }
Outcome: math12z

```

```

Treatment-effects estimation      Number of obs      =      5,671
Estimator      : propensity-score matching      Matches: requested =      1
Outcome model   : matching                      min =      1
Treatment model: logit                      max =      1

```

	Coefficient	AI robust std. err.	z	P> z	[95% conf. interval]	
ATET						
catholic						
(yes vs no)	.1237879	.0439014	2.82	0.005	.0377427	.209833

Outcome: read12z

```

Treatment-effects estimation      Number of obs      =      5,671
Estimator      : propensity-score matching      Matches: requested =      1
Outcome model   : matching                      min =      1
Treatment model: logit                      max =      1

```

	Coefficient	AI robust std. err.	z	P> z	[95% conf. interval]	
ATET						
catholic						
(yes vs no)	.1081204	.0455281	2.37	0.018	.018887	.1973538

Outcome: hsgrad

```

Treatment-effects estimation      Number of obs      =      5,671
Estimator      : propensity-score matching      Matches: requested =      1
Outcome model   : matching                      min =      1
Treatment model: logit                      max =      1

```

	Coefficient	AI robust std. err.	z	P> z	[95% conf. interval]	
ATET						
catholic						
(yes vs no)	.0236486	.0117346	2.02	0.044	.0006492	.0466481

Outcome: inpse

```

Treatment-effects estimation      Number of obs      =      5,671
Estimator      : propensity-score matching      Matches: requested =      1
Outcome model   : matching                      min =      1
Treatment model: logit                      max =      1

```

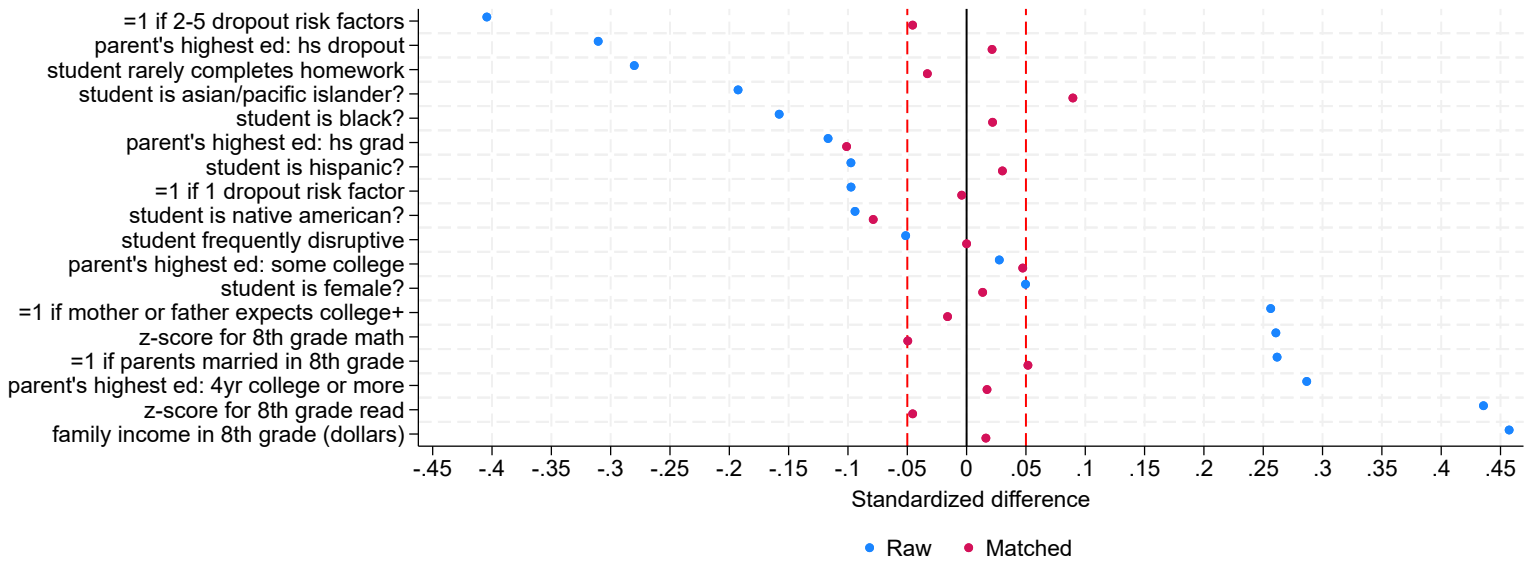
	Coefficient	AI robust std. err.	z	P> z	[95% conf. interval]	
ATET						
catholic						
(yes vs no)	.0793919	.0220244	3.60	0.000	.0362248	.122559

```

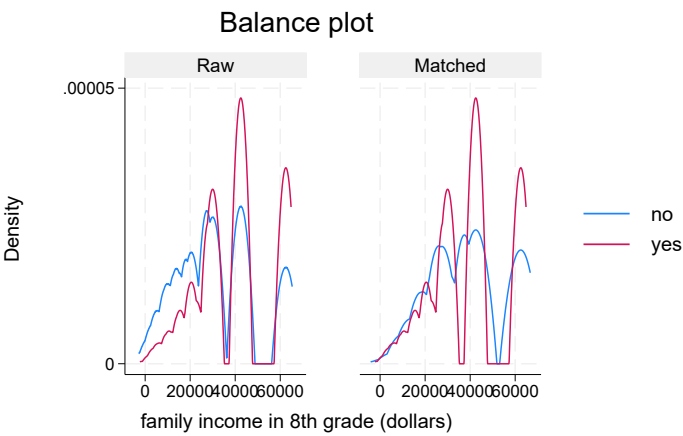
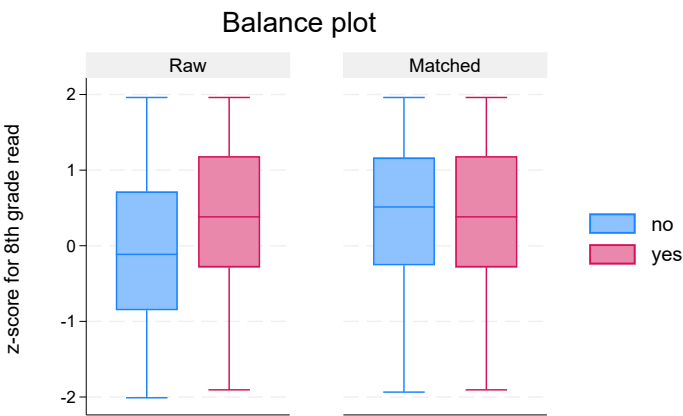
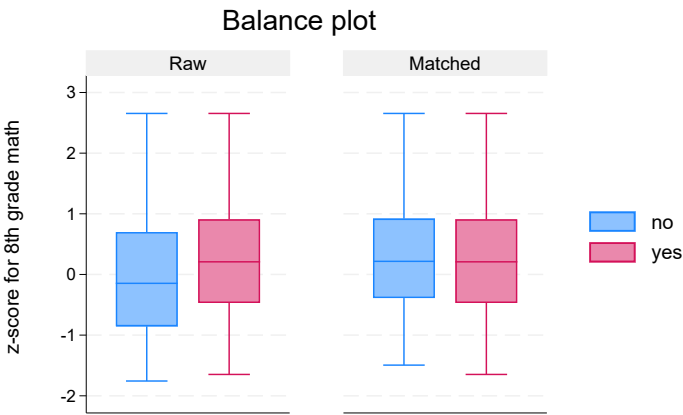
. // Close log and convert to PDF
. capture log close

```

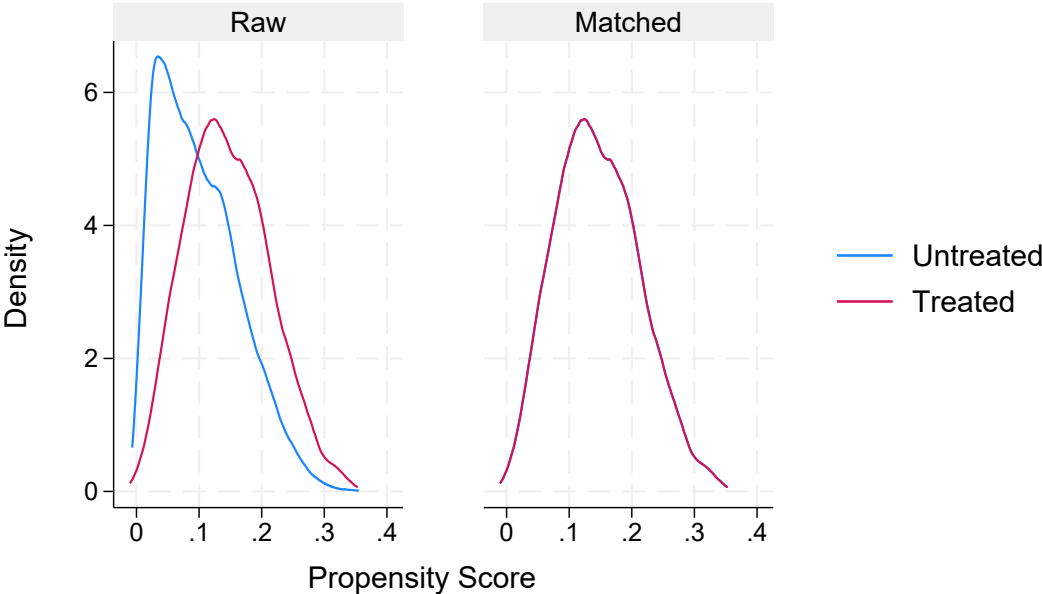
Standardized differences: raw and matched



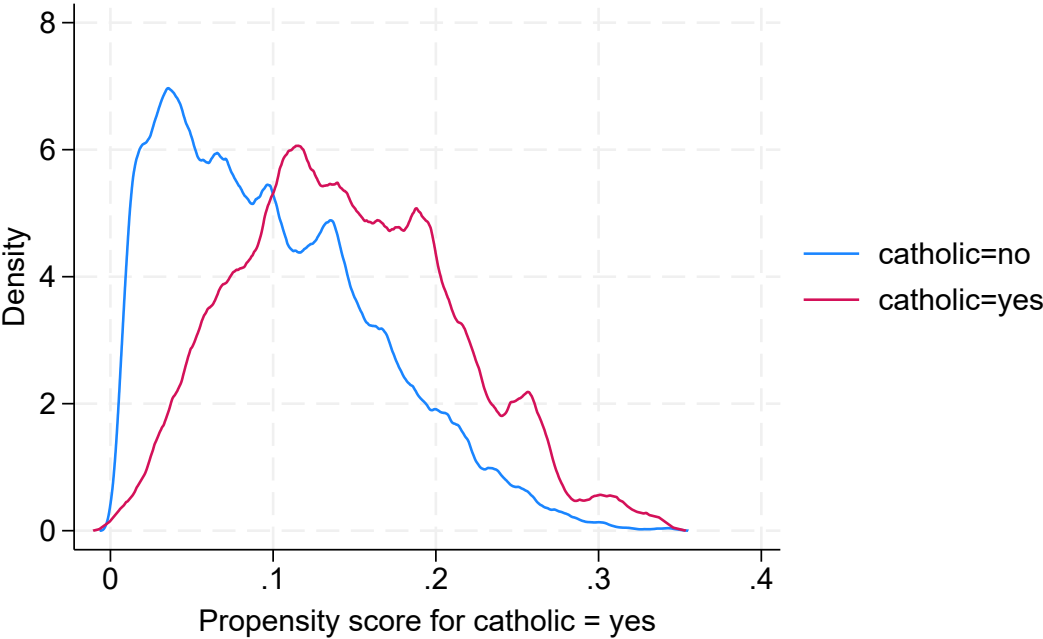
Covariate balance: after teffects psmatch



Propensity score distribution: all observations and matched sample



Propensity score distribution: all observations using teoverlap



	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	math12z	read12z	hsgrad	inpse	math12z	math12z	read12z	read12z	hsgrad	hsgrad	inpse	inpse
main												
r1vs0.catholic	0.0976* (0.0390)	-0.0279 (0.0394)	0.0169 (0.0108)	0.0676** (0.0209)	0.119*** (0.0231)	0.110* (0.0527)	0.0399 (0.0278)	0.0361 (0.0585)	0.0221** (0.00714)	0.0307 (0.0197)	0.0621*** (0.0149)	0.127*** (0.0202)
POmean												
0.catholic					0.248*** (0.0318)	-0.0124 (0.0135)	0.288*** (0.0293)	-0.00417 (0.0136)	0.953*** (0.00382)	0.915*** (0.00382)	0.799*** (0.00893)	0.703*** (0.00628)
TME1												
math8z					-0.0631 (0.0720)	-0.0631 (0.0720)	-0.0631 (0.0720)	-0.0631 (0.0720)	-0.0631 (0.0720)	-0.0631 (0.0720)	-0.0631 (0.0720)	-0.0631 (0.0720)
c.math8z#c.math8z					-0.169*** (0.0504)	-0.169*** (0.0504)	-0.169*** (0.0504)	-0.169*** (0.0504)	-0.169*** (0.0504)	-0.169*** (0.0504)	-0.169*** (0.0504)	-0.169*** (0.0504)
read8z					0.322*** (0.0681)	0.322*** (0.0681)	0.322*** (0.0681)	0.322*** (0.0681)	0.322*** (0.0681)	0.322*** (0.0681)	0.322*** (0.0681)	0.322*** (0.0681)
c.read8z#c.read8z					0.0105 (0.0490)	0.0105 (0.0490)	0.0105 (0.0490)	0.0105 (0.0490)	0.0105 (0.0490)	0.0105 (0.0490)	0.0105 (0.0490)	0.0105 (0.0490)
female					0.0409 (0.0938)	0.0409 (0.0938)	0.0409 (0.0938)	0.0409 (0.0938)	0.0409 (0.0938)	0.0409 (0.0938)	0.0409 (0.0938)	0.0409 (0.0938)
black					-0.249 (0.190)	-0.249 (0.190)	-0.249 (0.190)	-0.249 (0.190)	-0.249 (0.190)	-0.249 (0.190)	-0.249 (0.190)	-0.249 (0.190)
hisp					-0.0946 (0.158)	-0.0946 (0.158)	-0.0946 (0.158)	-0.0946 (0.158)	-0.0946 (0.158)	-0.0946 (0.158)	-0.0946 (0.158)	-0.0946 (0.158)
api					-1.176*** (0.284)	-1.176*** (0.284)	-1.176*** (0.284)	-1.176*** (0.284)	-1.176*** (0.284)	-1.176*** (0.284)	-1.176*** (0.284)	-1.176*** (0.284)
nativam					-0.488 (0.283)	-0.488 (0.283)	-0.488 (0.283)	-0.488 (0.283)	-0.488 (0.283)	-0.488 (0.283)	-0.488 (0.283)	-0.488 (0.283)
riskdrop1					0.0250 (0.118)	0.0250 (0.118)	0.0250 (0.118)	0.0250 (0.118)	0.0250 (0.118)	0.0250 (0.118)	0.0250 (0.118)	0.0250 (0.118)
riskdrop2					-0.403 (0.245)	-0.403 (0.245)	-0.403 (0.245)	-0.403 (0.245)	-0.403 (0.245)	-0.403 (0.245)	-0.403 (0.245)	-0.403 (0.245)
disrupt8					0.222 (0.128)	0.222 (0.128)	0.222 (0.128)	0.222 (0.128)	0.222 (0.128)	0.222 (0.128)	0.222 (0.128)	0.222 (0.128)
nohw8					-0.627*** (0.177)	-0.627*** (0.177)	-0.627*** (0.177)	-0.627*** (0.177)	-0.627*** (0.177)	-0.627*** (0.177)	-0.627*** (0.177)	-0.627*** (0.177)
faminc8b					0.0000294 (0.000015)	0.0000294 (0.000015)	0.0000294 (0.000015)	0.0000294 (0.000015)	0.0000294 (0.000015)	0.0000294 (0.000015)	0.0000294 (0.000015)	0.0000294 (0.000015)
c.faminc8b#c.faminc8b					-2.06e-10 (1.79e-10)	-2.06e-10 (1.79e-10)	-2.06e-10 (1.79e-10)	-2.06e-10 (1.79e-10)	-2.06e-10 (1.79e-10)	-2.06e-10 (1.79e-10)	-2.06e-10 (1.79e-10)	-2.06e-10 (1.79e-10)
pared1					-0.623 (0.318)	-0.623 (0.318)	-0.623 (0.318)	-0.623 (0.318)	-0.623 (0.318)	-0.623 (0.318)	-0.623 (0.318)	-0.623 (0.318)
pared2					0.0492 (0.205)	0.0492 (0.205)	0.0492 (0.205)	0.0492 (0.205)	0.0492 (0.205)	0.0492 (0.205)	0.0492 (0.205)	0.0492 (0.205)
pared3					0.129 (0.206)	0.129 (0.206)	0.129 (0.206)	0.129 (0.206)	0.129 (0.206)	0.129 (0.206)	0.129 (0.206)	0.129 (0.206)

pared4					0.323 (0.201)	0.323 (0.201)	0.323 (0.201)	0.323 (0.201)	0.323 (0.201)	0.323 (0.201)	0.323 (0.201)	0.323 (0.201)
parmarried					0.260 (0.171)	0.260 (0.171)	0.260 (0.171)	0.260 (0.171)	0.260 (0.171)	0.260 (0.171)	0.260 (0.171)	0.260 (0.171)
collegexp					0.277 (0.146)	0.277 (0.146)	0.277 (0.146)	0.277 (0.146)	0.277 (0.146)	0.277 (0.146)	0.277 (0.146)	0.277 (0.146)
_cons					-3.234*** (0.387)	-3.234*** (0.387)	-3.234*** (0.387)	-3.234*** (0.387)	-3.234*** (0.387)	-3.234*** (0.387)	-3.234*** (0.387)	-3.234*** (0.387)
N	5671	5671	5671	5671	5671	5671	5671	5671	5671	5671	5671	5671

Standard errors in parentheses  
="\* p<0.05                \*\* p<0.01   \*\*\* p<0.001"