Step-by-Step Guidelines for Propensity Score Weighting with Two Groups

Beth Ann Griffin

Four key steps

1) Choose the primary treatment effect of interest (ATE or ATT)

2) Estimate propensity score (ps) weights

3) Evaluate the quality of the ps weights

4) Estimate the treatment effect

Case study

- **Aim:** To estimate the causal effect of MET/CBT5 versus "usual care"
  - Data from 2 SAMSHA CSAT discretionary grants

MET/CBT5	"Usual Care"
• Longitudinal, observational	• Longitudinal, observational
• 37 sites from EAT study	• 4 sites from ATM study
• N = 2459	• N = 444
• 2003/04 - 2007	• 1998-1999

Case study

- Aim: To estimate the causal effect of MET/CBT5 versus "usual care"
  - Data from 2 SAMSHA CSAT discretionary grants

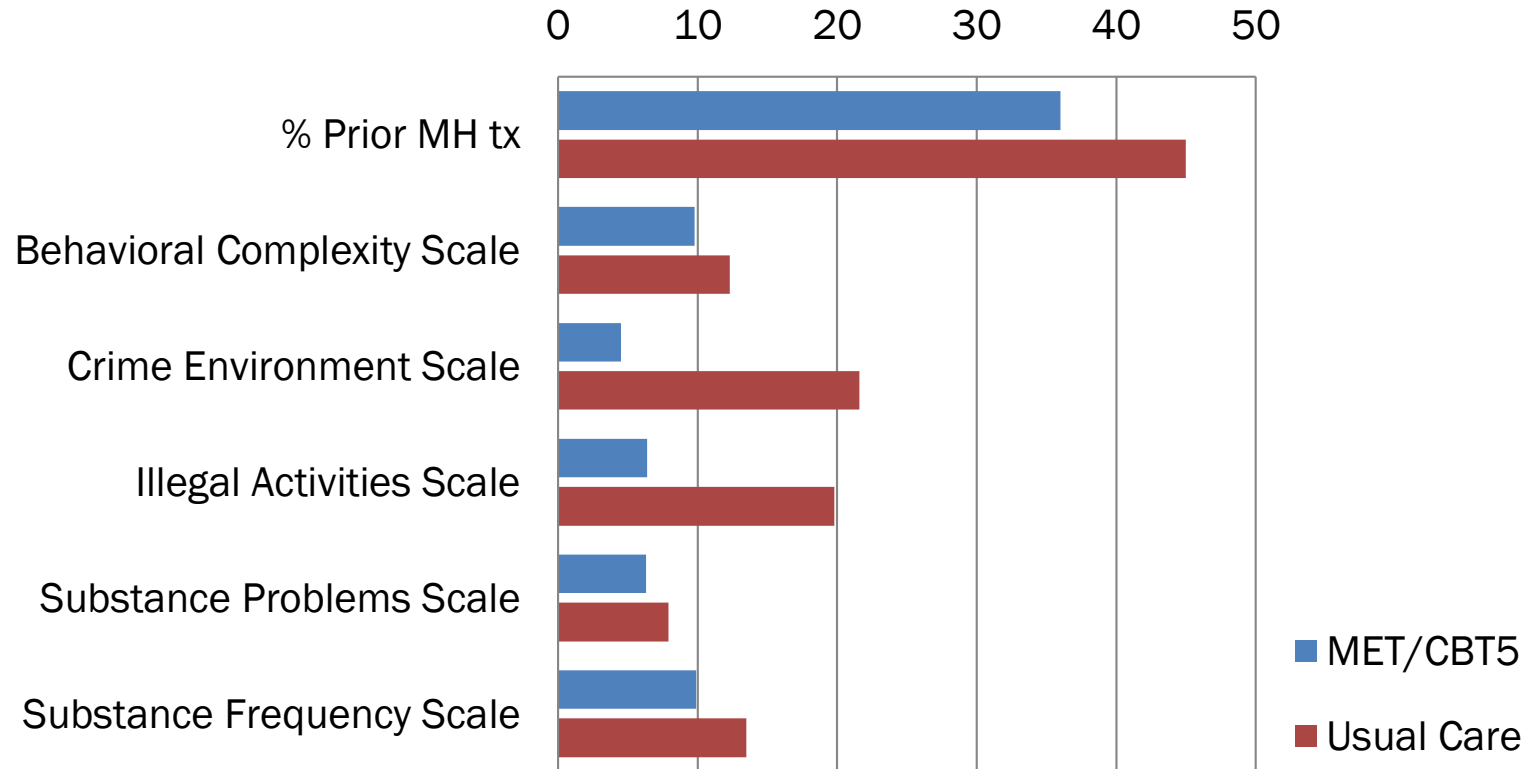| MET/CBT5	"Usual Care"
• Longitudinal, observational	• Longitudinal, observational
• 37 sites from EAT study	• 4 sites from ATM study
• N = 2459	• N = 444
• 2003/04 - 2007	• 1998-1999

All youth assessed with the GAIN at baseline, 6 months, and 12 months

Selection exists: Various meaningful ways in which the groups differ

Step 1: Choose the primary treatment effect (ATE or ATT)

- Today, we chose to focus on estimating an ATT-type estimand
  - Want to draw inferences about the effect of treatment for individuals in the control condition (so really ATC)
  - In this case, we can just flip treatment indicator so 1 = usual care and 0 = MET/CBT5 to get the needed ATT estimand for the control group

- Why?
  - Youth in the community are different from those targeted to receive MET/CBT5 in the EAT study
  - Thus, the policy question we want to address is

How would youth like those receiving
"usual care" in the community have fared
had they received MET/CBT5?

Step 2: Estimate the ps weights

- Only 1 command needed for this step

- Binary treatment command in TWANG currently available in R, SAS and STATA

- Shiny available soon (will showcase beta version at end of this session)

Command to estimate ps weights in Stata

- use aod_big,clear
- ps atm age female i.race4g sfs sps sds ias ces eps imds bcs prmhtx, ///
  ntrees(5000) stopmethod(es.max) estimand(ATT) ///
  rcmd(C:\Program Files\R\R-3.0.3\bin\Rscript.exe) ///
  objpath(C:\Users\sliu002\Desktop\twang\webinar twang) ///
  plotname(binary_twang_att.pdf)
- balance, unweighted weighted
- save subdata_twogrp_att_wgts,replace

Command to estimate ps weights in Stata

Specifies name of treatment variable (for ATT, it should = targeted group)

· use abd_big,clear
· ps **atm** age female i.race4g sfs sps sds ias ces eps imds bcs prmhtx, ///
  ntrees(5000) stopmethod(es.max) estimand(ATT) ///
  rcmd(C:\Program Files\R\R-3.0.3\bin\Rscript.exe) ///
  objpath(C:\Users\sliu002\Desktop\twang\webinar twang) ///
  plotname(binary_twang_att.pdf)
· balance, unweighted weighted
· save subdata_twogrp_att_wgts,replace

Command to estimate ps weights in Stata

- use aod_big,clear
- ps atm **age female i.race4g sfs sps sds ias ces eps imds bcs prmhtx,** ///
  ntrees(5000) stopmethod(es.max) estimand(ATT) , ///
  rcmd(C:\Program Files\R\R-3.0.3\bin\Rscript.exe) ///
  objpath(C:\Users\sliu002\Desktop\twang\   /
  plotname(binary_twang_att.pdf)
- balance, unweighted weighted
- save subdata_twogrp_att_wgts,replace

Specifies list of pretreatment covariates to balance on

Command to estimate ps weights in Stata

Specifies categorical variable race4g as i.race4g

- use aod_big,clear
- ps atm age female **i.race4g** sfs sps sds ias ces eps imds bcs prmhtx, ///
  ntrees(5000) stopmethod(es.max) estimand(ATT) ///
  rcmd(C:\Program Files\R\R-3.0.3\bin\Rscript.exe) ///
  objpath(C:\Users\sliu002\Desktop\twang\webinar twang) ///
  plotname(binary_twang_att.pdf)
- balance, unweighted weighted
- save subdata_twogrp_att_wgts,replace

Command to estimate ps weights in Stata

- **use aod_big,clear** ← **Specifies name of dataset**
- ps atm age female i.race4g sfs sps sds ias ces eps imds bcs prmhtx, ///
  ntrees(5000) stopmethod(es.max) estimand(ATT) ///
  rcmd(C:\Program Files\R\R-3.0.3\bin\Rscript.exe) ///
  objpath(C:\Users\sliu002\Desktop\twang\webinar twang) ///
  plotname(binary_twang_att.pdf)
- balance, unweighted weighted
- save subdata_twogrp_att_wgts,replace

Command to estimate ps weights in Stata

· use aod_big,clear
· ps atm age female i.race4g sfs sps sds ias ces eps imds
  bcs prmhtx, ///
  ntrees(5000) stopmethod(es.max) estimand(ATT) ///
  rcmd(C:\Program Files\R\R-3.0.3\bin\Rscript.exe) ///
  objpath(C:\Users\sliu002\Desktop\twang\webinar twang) ///
  plotname(binary_twang_att.pdf)
· balance, unweighted weighted
· save subdata_twogrp_att_wgts,replace

Specifies the maximum number of iterations used by GBM. Should be large (5000 to 10000)

Command to estimate ps weights in Stata

- use aod_big,clear
- ps atm age female i.race4g sfs sps sds ias ces eps imds
  bcs prmhtx, ///
  ntrees(5000) **stopmethod(es.max)** estimand(ATT) ///
  rcmd(C:\Program Files\R\R-3.0.?\bin\Rscript.exe) ///
  objpath(C:\Users\sliu002\Desktop\twang\webinar twang) ///
  plotname(binary_twang_att.pdf)
- balance, unweighted weighted
- save subdata_twogrp_att_wgts,replace

Specifies the criteria for choosing the optimal number of iterations. Available choices include mean or max ES and mean or max KS statistics
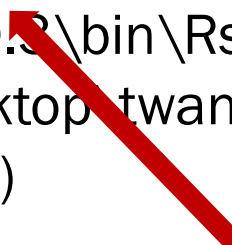
Command to estimate ps weights in Stata

- use aod_big,clear
- ps atm age female i.race4g sfs sps sds ias ces eps imds
  bcs prmhtx, ///
  ntrees(5000) stopmethod(es.max) **estimand(ATT)** ///
  rcmd(C:\Program Files\R\R-3.0.3\bin\Rscript.exe) ///
  objpath(C:\Users\sliu002\Desktop\twang\webinar twang) ///
  plotname(binary_twang_att.pdf)
- balance, unweighted weighted
- save subdata_twogrp_att_wgts,replace

Specifies primary estimand of interest (ATT or ATE)

Command to estimate ps weights in SAS

· use aod_big,clear

· ps atm age female i.race4g sfs sps sds ias ces eps imds bcs prmhtx, ///
  ntrees(5000) stopmethod(es.max) estimand(ATT) ///
  rcmd(C:\Program Files\R\R-3.0.3\bin\Rscript.exe) ///
  objpath(C:\Users\sliu002\Desktop\twang\webinar twang) ///
  plotname(binary_twang_att.pdf)

· balance, unweighted weighted

· **save subdata_twogrp_att_wgts,replace**   ⬅

Specifies name of outputted dataset with ps weights

Command to estimate ps weights in SAS

- use aod_big,clear
- ps atm age female i.race4g sfs sps sds ias ces eps imds
  bcs prmhtx, ///
  ntrees(5000) stopmethod(es.max) estimand(ATT) ///
  rcmd(C:\Program Files\R\R-3.0.3\bin\Rscript.exe) ///
  objpath(C:\Users\sliu002\Desktop\twang\webinar twang) ///
  plotname(binary_twang_att.pdf)
- balance, unweighted weighted
- save subdata_twogrp_att_wgts,replace

Specifies the R executable by name and path

Command to estimate ps weights in Stata

- use aod_big,clear
- ps atm age female i.race4g sfs sps sds ias ces eps imds
  bcs prmhtx, ///
  ntrees(5000) stopmethod(es.max) estimand(ATT) ///
  rcmd(C:\Program Files\R\R-3.0.3\bin\Rscript.exe) ///
  objpath(C:\Users\sliu002\Desktop\twang\webinar twang) ///
  plotname(binary_twang_att.pdf) ⬅ **Specifies name of file where diagnostic plots will go**
- balance, unweighted weighted
- save subdata_twogrp_att_wgts,replace

Command to estimate ps weights in Stata

- use aod_big,clear
- ps atm age female i.race4g sfs sps sds ias ces eps imds
  bcs prmhtx, ///
  ntrees(5000) stopmethod(es.max) estimand(ATT) ///
  rcmd(C:\Program Files\R\R-3.0.3\bin\Rscript.exe) ///
  objpath(C:\Users\sliu002\Desktop\twang\webinar twang) ///
  plotname(binary_twang_att.pdf)
- balance, unweighted weighted
- save subdata_twogrp_att_wgts,replace

Specifies folder where outputted data and plots will go

Command to estimate ps weights in SAS

- use aod_big,clear
- ps atm age female i.race4g sfs sps sds ias ces eps imds bcs prmhtx, ///
  ntrees(5000) stopmethod(es.max) estimand(ATT) ///
  rcmd(C:\Program Files\R\R-3.0.3\bin\Rscript.exe) ///
  objpath(C:\Users\sliu002\Desktop\twang\webinar twang) ///
  plotname(binary_twang_att.pdf)
- **balance, unweighted weighted** ⟵
- save subdata_twogrp_att_wgts,replace

Print unweighted and weighted balance tables in the output window

Step 3: Evaluate the quality of the ps weights

- Key issues that should be checked:
  - Convergence = did the algorithm run long enough
  - Balance = how well matched the two groups look after weighting
  - Overlap = whether there is evidence that the distributions of the pretreatment covariates in the two groups line up well

Step 3: Checking convergence

Bad Convergence
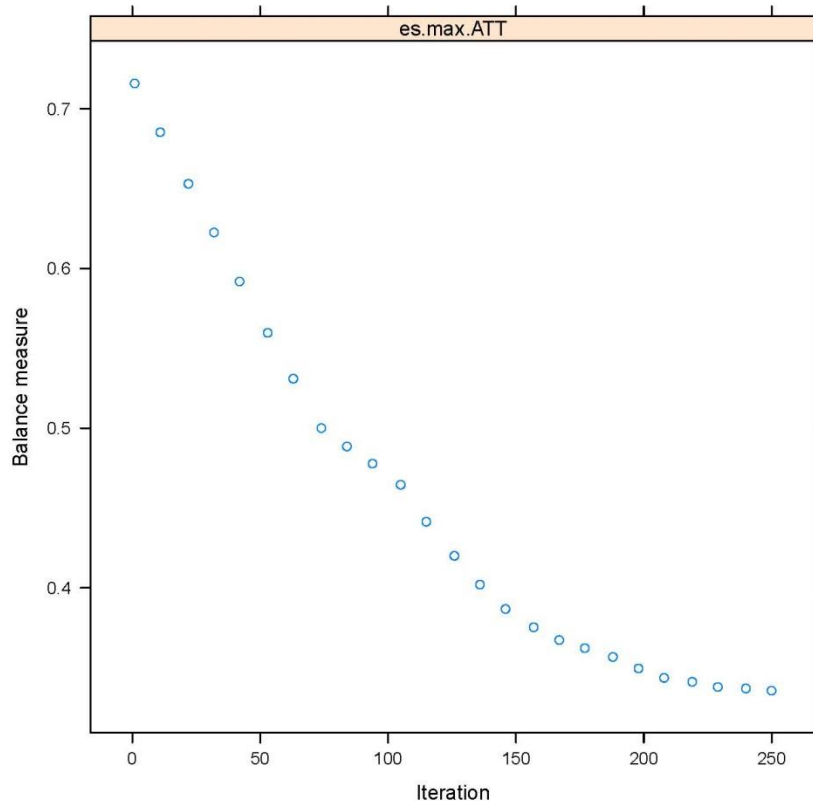
Good Convergence
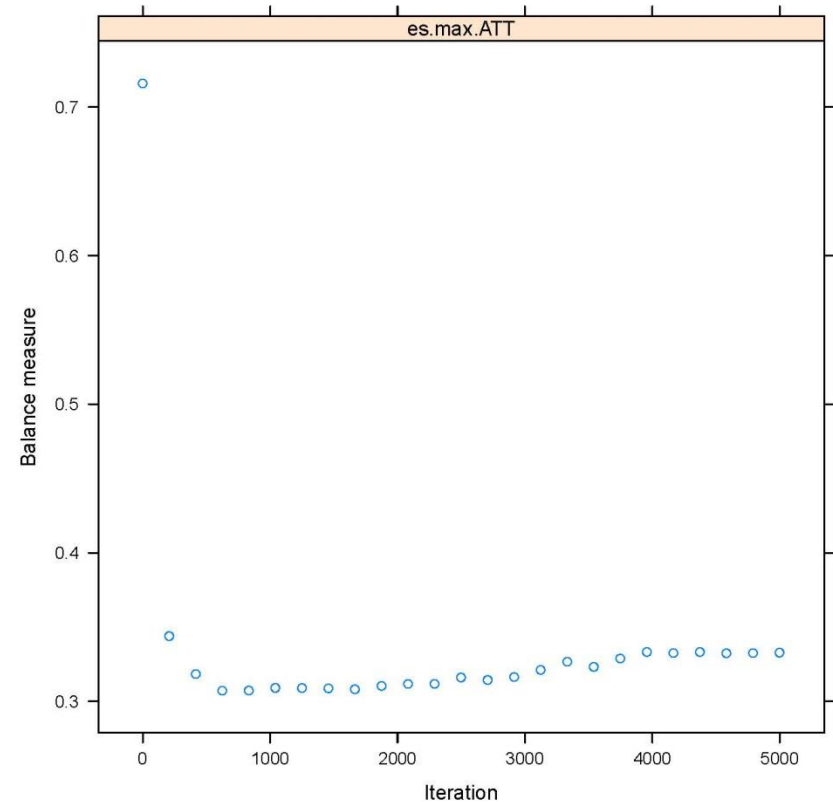
Step 3: Checking balance

- TWANG has numerous diagnostics for assessing balance

Step 3: Checking balance with tables

Step 3: Checking balance with tables
Unweighted balance table

Unweighted

	txmn	txsd	ctmn	ctsd	stdeffsz	stat	p	ks	kspval
_									
age	15.82	1.088	15.54	1.573	.255	4.59	0	.116	0
bcs	12.26	7.405	9.832	7.776	.328	6.309	0	.177	0
ces	.242	.363	.052	.177	.524	10.81	0	.262	0
eps	.279	.191	.208	.185	.373	7.267	0	.186	0
female	.214	.411	.315	.465	−.246	−4.666	0	.101	.001
ias	.224	.19	.087	.109	.719	14.73	0	.485	0
imds	7.723	8.234	7.831	8.515	−.013	−.253	.8	.03	.874
prmhtx	.449	.498	.367	.482	.164	3.202	.001	.082	.012
sds	3.099	2.332	2.338	2.22	.327	6.382	0	.147	0
sfs	.145	.147	.109	.123	.246	4.889	0	.12	0
sps	7.93	4.454	6.311	4.268	.364	7.1	0	.141	0
race4g									
1	.673	.469	.51	.5	.349	21.45	0	.163	0
2	.135	.342	.081	.273	.157	.	.	.054	0
3	.097	.296	.241	.428	−.487	.	.	.144	0
4	.092	.29	.168	.374	−.261	.	.	.076	0
Missingn~s									
bcs	0	0	.002	.049	−.054	−37.83	0	.002	.297
eps	0	0	.002	.04	−.044	−32.14	0	.002	.395
ias	0	0	.009	.094	−.103	−72.54	0	.009	.045
imds	0	0	.002	.04	−.044	−32.14	0	.002	.395
prmhtx	.002	.047	.007	.083	−.059	−1.093	.275	.005	.25
race4g	.002	.047	0	0	.048	.	.	.002	0
sds	0	0	.004	.06	−.066	−47.38	0	.004	.201
sps	0	0	.001	.035	−.038	−27.37	0	.001	.461

Step 3: Checking balance with tables Unweighted balance table

Unweighted

	txmn	txsd	ctmn	ctsd	stdeffsz	stat	p	ks	kspval
age	15.82	1.088	15.54	1.573	.255	4.59	0	.116	0
bcs	12.26	7.405	9.832	7.776	.328	6.309	0	.177	0
ces	.242	.363	.052	.177	.524	10.81	0	.262	0
eps	.279	.191	.208	.185	.373	7.267	0	.186	0
female	.214	.411	.315	.465	−.246	−4.666	0	.101	.001
ias	.224	.19	.087	.109	.719	14.73	0	.485	0
imds	7.723	8.234	7.831	8.515	−.013	−.253	.8	.03	.874
prmhtx	.449	.498	.367	.482	.164	3.202	.001	.082	.012
sds	3.099	2.332	2.338	2.22	.327	6.382	0	.147	0
sfs	.145	.147	.109	.123	.246	4.889	0	.12	0
sps	7.93	4.454	6.311	4.268	.364	7.1	0	.141	0
race4g									
1	.673	.469	.51	.5	.349	21.45	0	.163	0
2	.135	.342	.081	.273	.157	.	.	.054	0
3	.097	.296	.241	.428	−.487	.	.	.144	0
4	.092	.29	.168	.374	−.261	.	.	.076	0
Missingn~s									
bcs	0	0	.002	.049	−.054	−37.83	0	.002	.297
eps	0	0	.002	.04	−.044	−32.14	0	.002	.395
ias	0	0	.009	.094	−.103	−72.54	0	.009	.045
imds	0	0	.002	.04	−.044	−32.14	0	.002	.395
prmhtx	.002	.047	.007	.083	−.059	−1.093	.275	.005	.25
race4g	.002	.047	0	0	.048	.	.	.002	0
sds	0	0	.004	.06	−.066	−47.38	0	.004	.201
sps	0	0	.001	.035	−.038	−27.37	0	.001	.461

Highlights denotes rows with absolute ES > 0.10

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Step 3: Checking balance with tables
# Weighted balance table

```
Weighted: esmax
```

	txmn	txsd	ctmn	ctsd	stdeffsz	stat	p	ks	kspval
—									
age	15.82	1.088	15.8	1.459	.019	.238	.812	.052	.524
bcs	12.26	7.405	12.48	7.757	−.03	−.466	.641	.06	.351
ces	.242	.363	.131	.284	.305	4.32	0	.152	0
eps	.279	.191	.255	.183	.124	2.056	.04	.064	.283
female	.214	.411	.248	.432	−.084	−1.311	.19	.035	.929
ias	.224	.19	.203	.169	.107	1.67	.095	.083	.073
imds	7.723	8.234	8.396	8.509	−.082	−1.262	.207	.062	.308
prmhtx	.449	.498	.453	.498	−.008	−.129	.898	.004	1
sds	3.099	2.332	2.898	2.245	.086	1.312	.19	.049	.6
sfs	.145	.147	.148	.144	−.019	−.283	.778	.049	.605
sps	7.93	4.454	7.561	4.249	.083	1.272	.204	.052	.522
race4g									
1	.673	.469	.666	.472	.016	1.083	.362	.007	.362
2	.135	.342	.105	.307	.087	.	.	.03	.362
3	.097	.296	.12	.325	−.079	.	.	.023	.362
4	.092	.29	.108	.311	−.055	.	.	.016	.362
Missingn~s									
bcs	0	0	0	.013	−.004	−21.96	0	0	.125
eps	0	0	0	.005	−.001	−30.06	0	0	.029
ias	0	0	0	.012	−.002	−72.29	0	0	0
imds	0	0	0	.005	−.001	−30.06	0	0	.029
prmhtx	.002	.047	.003	.053	−.007	−.212	.832	.001	.832
race4g	.002	.047	0	0	.048	.	.	.002	.362
sds	0	0	.002	.041	−.03	−42.25	0	.002	.004
sps	0	0	0	.011	−.004	−20.27	0	0	.151

Highlights denote rows with absolute ES > 0.10

Step 3: Checking balance graphically

Step 3: Checking balance graphically ES plot
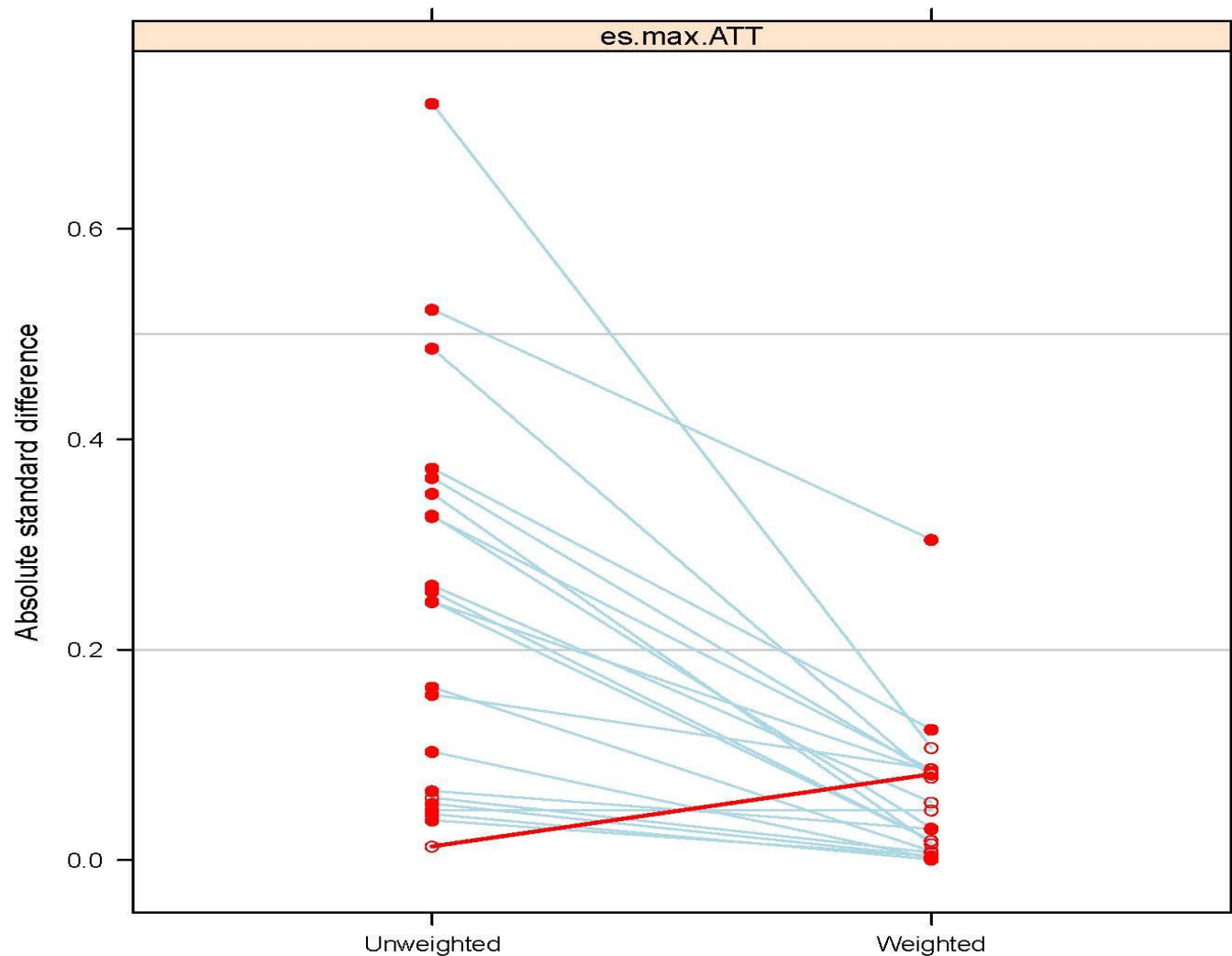
Step 3: Checking balance graphically ES plot
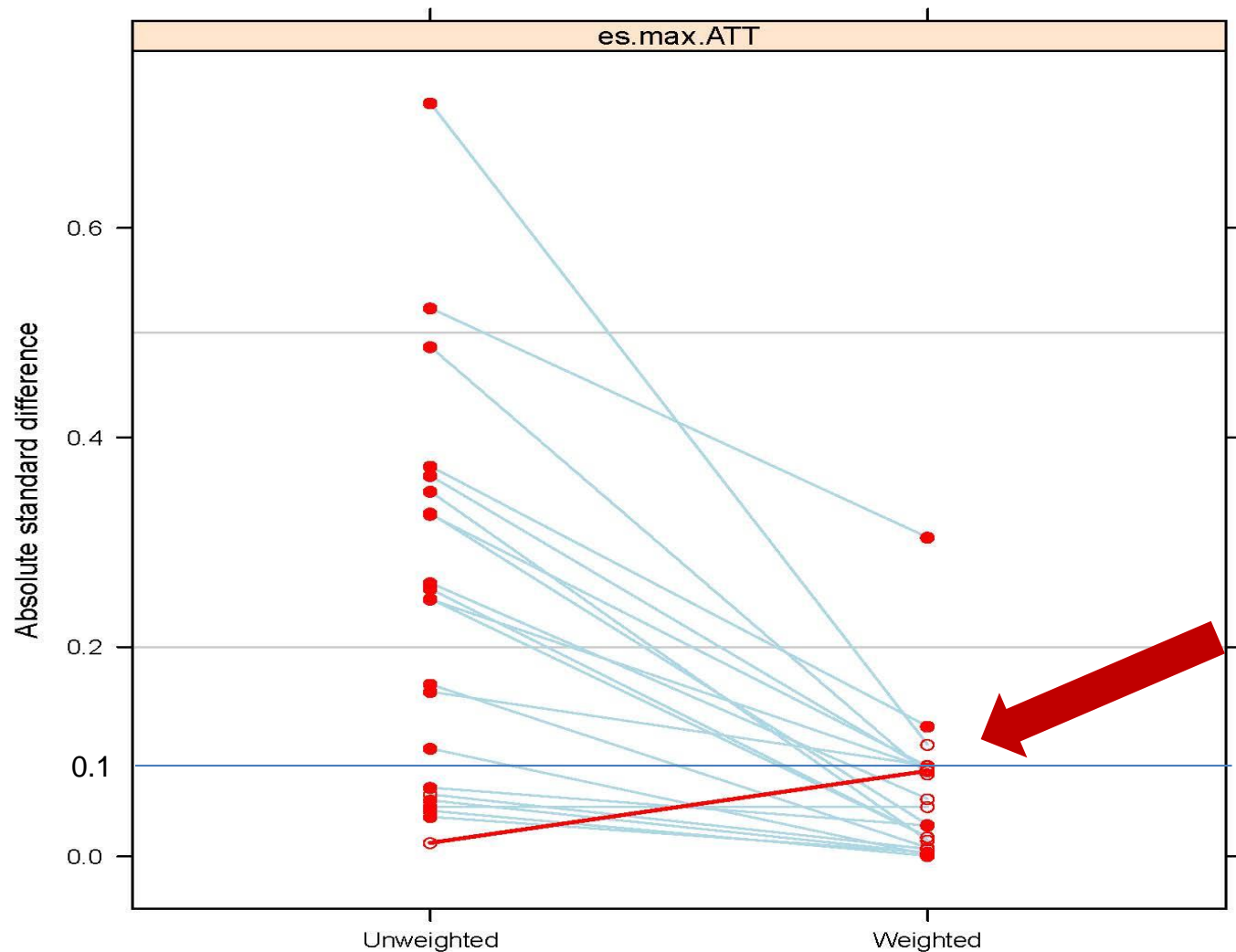
Want as many dots as possible to go below 0.10 after weighting

Step 3: Checking balance graphically KS plot

Plot 5 (ks): K–S P–values of Group Distns of Covariates
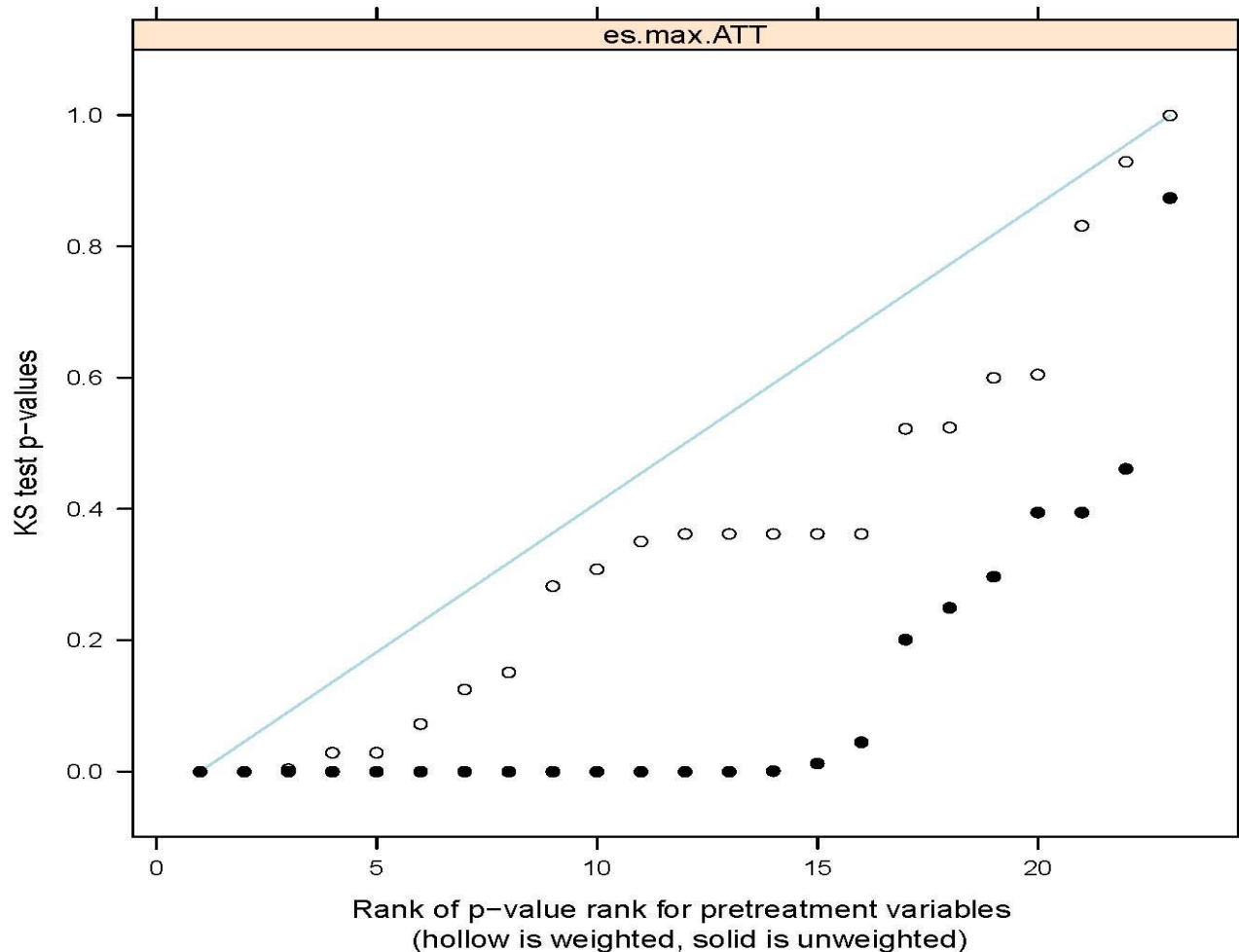
Step 3: Checking balance graphically KS plot

Plot 5 (ks): K–S P–values of Group Distns of Covariates
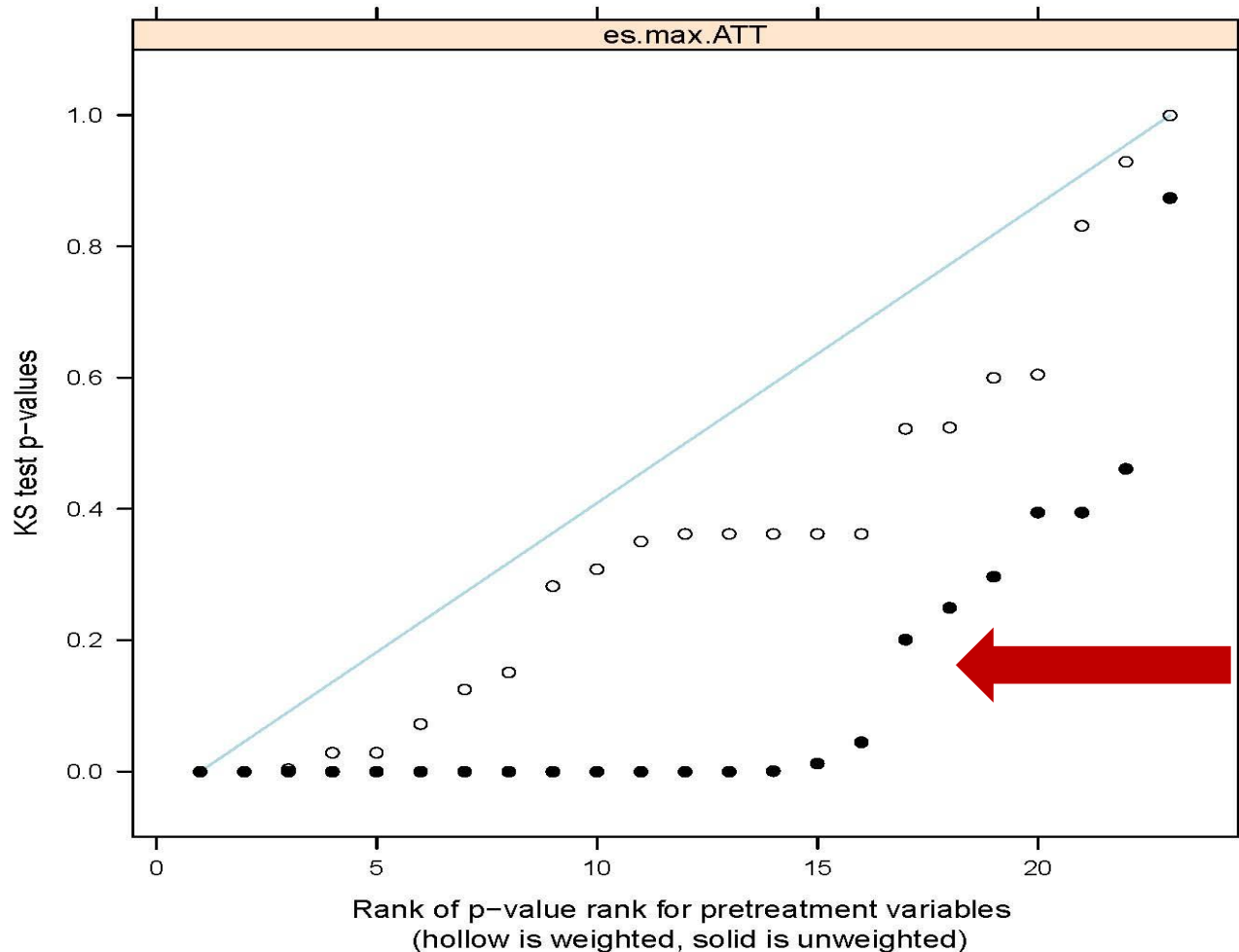
Solid dots = unweighted p-values. Note many less than 0.05

Step 3: Checking balance graphically KS plot

Plot 5 (ks): K–S P–values of Group Distns of Covariates
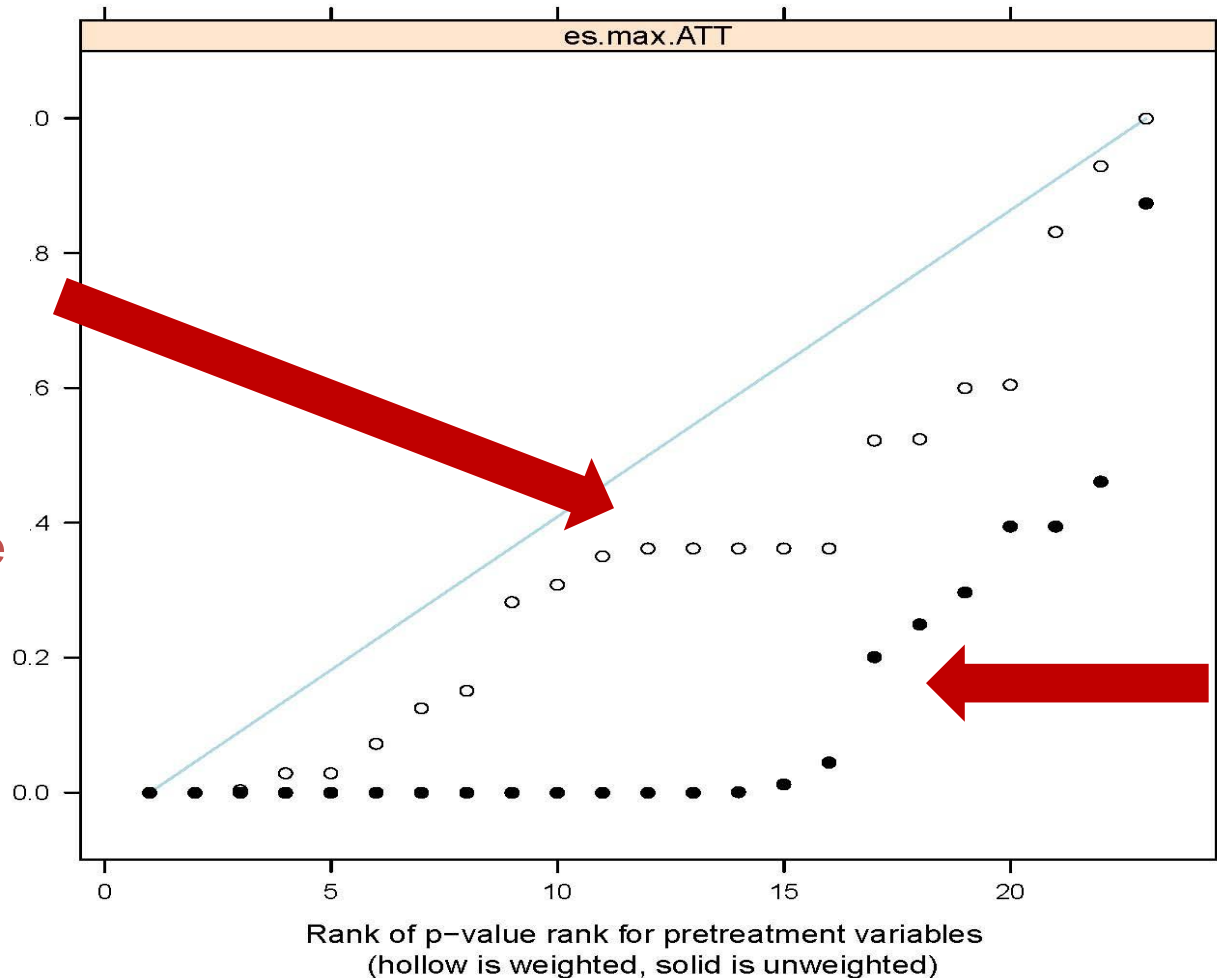
Open dots = weighted p-values. Note getting larger and moving towards the diagonal line

Solid dots = unweighted p-values. Note many less than 0.05

es.max.ATT

Rank of p-value rank for pretreatment variables
(hollow is weighted, solid is unweighted)

Step 3: Checking overlap
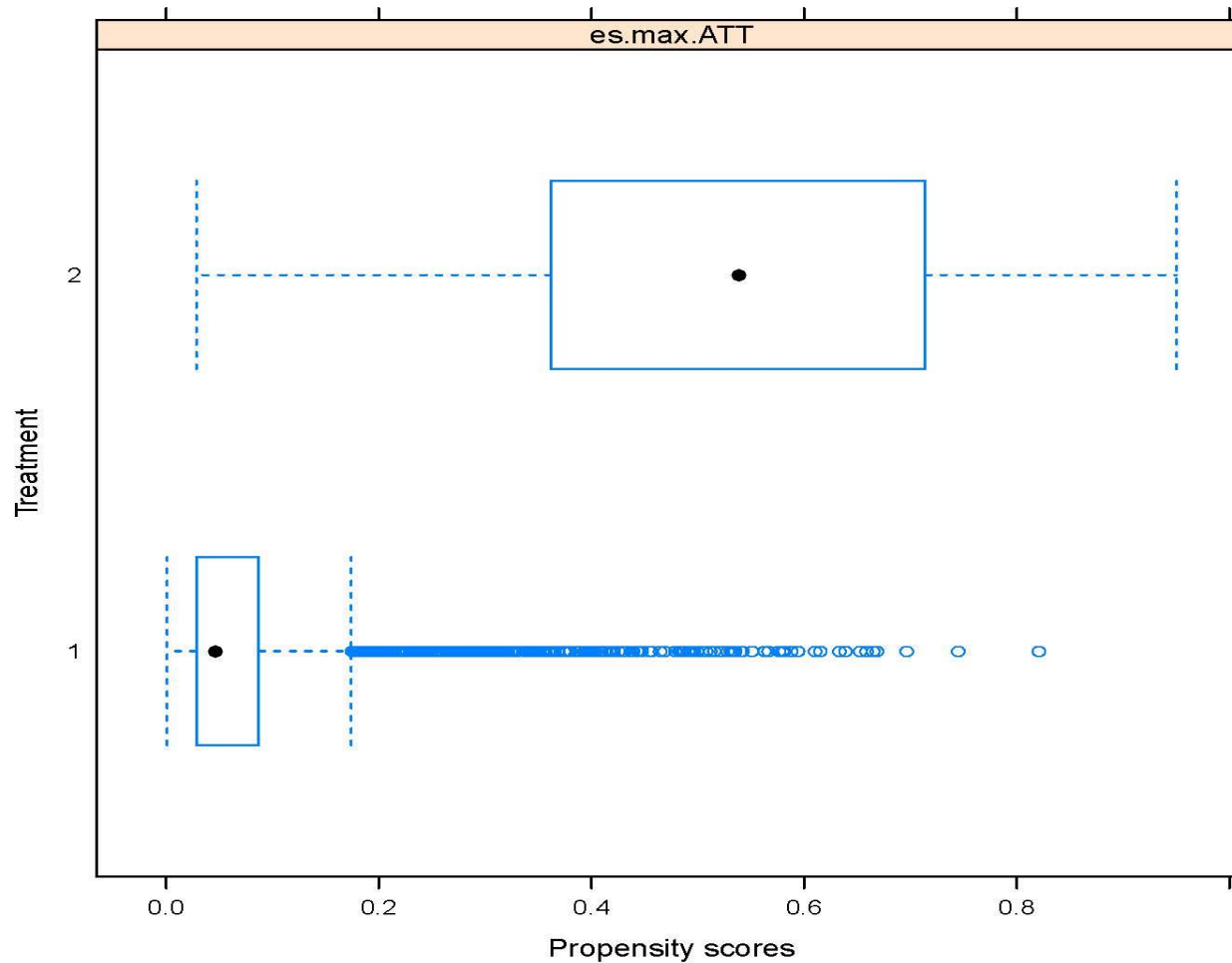
Step 3: Checking overlap

Check for 0 (empty) cells on binary and categorical

	MET/CBT5	Usual Care
Female	774	95
Race = 1	1254	299
Race = 2	200	60
Race = 3	592	43
Race = 4	412	41
Prior MH trt	897	199

Compare the minimums and maximums

	MET/CBT5	Usual Care
SFS	(0, 0.71)	(0, 0.65)
SPS	(0, 16)	(0, 16)
SDS	(0, 7)	(0, 7)
IAS	(0, 1)	(0, 1)
CES	(0, 1)	(0, 1)
EPS	(0, 0.98)	(0, 0.99)
IMDS	(0, 41)	(0, 34)
BCS	(0, 31)	(0, 31)

Note: We haven't even begun to talk about the outcome yet

- Steps 1 to 3 do not involve any outcomes

- We first focus on dealing with selection/pre-treatment group differences

- Then, if we do a good job, we will move to outcome analyses

Step 4: Estimate the treatment effect

- Estimate as difference in propensity score weighted means between the two groups of interest
  - Since we are using weights, we need to adjust our standard errors for the weighting
  - Analogous to fitting regression models with survey data with survey weights

Step 4: Estimate the treatment effect

- Estimate as difference in propensity score weighted means between the two groups of interest

  – Since we are using weights, we need to adjust our standard errors for the weighting

  – Analogous to fitting regression models with survey data with survey weights

We can use survey analysis commands in any software to estimate treatment effects

Step 4: Estimate the treatment effect (cont.)

Stata Code:

· use subdata_twogrp_att_wgts,clear
· reg sfs8p12 metcbt5[pweight=esmaxatt]

```
(sum of wgt is    7.3694e+02)

Linear regression                              Number of obs =     2901
                                               F(  1,  2899) =     4.69
                                               Prob > F      =   0.0304
                                               R-squared     =   0.0049
                                               Root MSE      =   .13845
```

sfs8p12	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf. Interval]	
metcbt5	-.0198438	.0091637	-2.17	0.030	-.0378119	-.0018758
_cons	.1141963	.0066653	17.13	0.000	.1011271	.1272656

Step 4: Estimate the treatment effect (cont.)

Stata Code:
· use subdata_twogrp_att_wgts,clear
· reg sfs8p12 metcbt5[pweight=esmaxatt]

```
(sum of wgt is   7.3694e+02)

Linear regression                          Number of obs =      2901
                                           F(  1,  2899) =      4.69
                                           Prob > F      =    0.0304
                                           R-squared     =    0.0049
                                           Root MSE      =    .13845
```

| | | Robust | | | | | |
sfs8p12	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]	
metcbt5	-.0198438	.0091637	-2.17	0.030	-.0378119	-.0018758
_cons	.1141963	.0066653	17.13	0.000	.1011271	.1272656

Results show that youth like those in "usual care" would have fared better had they received MET/CBT5

Comparison with unweighted treatment effect

Stata Code:
· use subdata_twogrp_att_wgts,clear
· reg sfs8p12 metcbt5

Source	SS	df	MS
Model	.832622997	1	.832622997
Residual	41.6553919	2899	.014368883
Total	42.4880148	2900	.01465104

Number of obs	=	2901
F(1, 2899)	=	57.95
Prob > F	=	0.0000
R-squared	=	0.0196
Adj R-squared	=	0.0193
Root MSE	=	.11987

sfs8p12	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]	
metcbt5	-.0470548	.0061815	-7.61	0.000	-.0591753	-.0349343
_cons	.1141963	.0056888	20.07	0.000	.1030419	.1253508

Comparison with unweighted treatment effect

Stata Code:

· use subdata_twogrp_att_wgts,clear

· reg sfs8p12 metcbt5

Source	SS	df	MS		
Model	.832622997	1	.832622997		
Residual	41.6553919	2899	.014368883		
Total	42.4880148	2900	.01465104		

Number of obs = 2901
$F(1, 2899)$ = 57.95
Prob > F = 0.0000
R-squared = 0.0196
Adj R-squared = 0.0193
Root MSE = .11987

sfs8p12	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]	
metcbt5	-.0470548	.0061815	-7.61	0.000	-.0591753	-.0349343
_cons	.1141963	.0056888	20.07	0.000	.1030419	.1253508

- **Also shows significant evidence that youth in "usual care" have higher substance use frequency at 12-months than those in MET/CBT5**

- **Magnitude of the effect unweighted is double (-0.02 vs -0.047)**

Step 4: Doubly robust estimation

- "Doubly robust" estimation is the preferred route for estimating causal treatment effects
  - Combines fitting a propensity score weighted regression model with the inclusion of additional pretreatment control covariates
  - As long as one piece is right (either the multivariate outcome model or the propensity score model), obtain consistent treatment effect estimates

Step 4: Doubly robust estimation: Adding in covariates with lingering imbalances

Stata Code:

· use subdata_twogrp_att_wgts,clear

· reg sfs8p12 metcbt5 ces [pweight=esmaxatt]

```
(sum of wgt is    7.3694e+02)
```

```
Linear regression                          Number of obs =      2901
                                           F( 2,  2898) =       2.67
                                           Prob > F     =     0.0693
                                           R-squared    =     0.0070
                                           Root MSE     =     .13832
```

| | | Robust | | | | |
sfs8p12	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]	
metcbt5	-.0219624	.0096355	-2.28	0.023	-.0408555	-.0030693
ces	-.0191335	.0161545	-1.18	0.236	-.050809	.012542
_cons	.118827	.0078169	15.20	0.000	.1034998	.1341542

Conclusions

- Use of propensity score weighting reduced bias in our treatment effect estimate

  - Greatly improved balance on observed pretreatment covariates

  - Magnitude of change went from 0.40 effect size difference to 0.20 effect size difference

- Use of propensity score weighting helped us produce more robust estimates of how youth like those in usual care would have fared had they received MET/CBT5

https://www.rand.org/statistics/twang.html

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Photo by Iz Marty / CC BY 2.0

The Toolkit for Weighting and Analysis of Nonequivalent Groups, or **TWANG**, contains a set of functions to support causal modeling of observational data through the estimation and evaluation of propensity score weights. The TWANG package was first developed in 2004 by RAND researchers for the R statistical computing language and environment. The R version of the package contains functions for creating high-quality propensity score weights which can be used to estimate treatment effects with two or more treatment groups and time-varying treatments.

In 2014, TWANG macros were developed for SAS and Stata to support the use of these tools

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Beth Ann Griffin
Senior Statistician

Beth Ann Griffin is a senior statistician at the RAND Corporation. Her research has largely focused on causal effects estimation when using observational data. Her substantive research has primarily fallen into three areas: (1) substance abuse treatment for adolescents, (2) the impact of...

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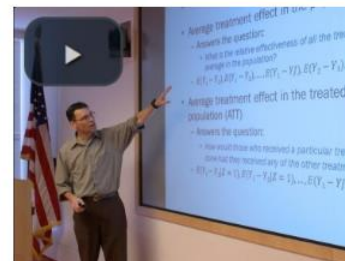
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