Title

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tebalance overid — Test for covariate balance

Description

tebalance overid performs a test for covariate balance after estimation by a teffects inverse-probability-weighted (IPW) estimator or an stteffects IPW estimator.

Quick start

Test for covariate balance after a teffects or an stteffects IPW estimator

    tebalance overid

As above, but test for balance only in base covariates and exclude interaction terms

    tebalance overid, bconly

Menu

Statistics > Treatment effects > Balance > Overidentification test

Syntax

> tebalance overid $\left[\,,\ \underline{\text{bconly}}\ \text{nolog}\ \underline{\text{iter}}\text{ate}(\#)\ \right]$

collect is allowed; see [U] **11.1.10 Prefix commands**.

Options

> ⌐ Main ⌐

bconly specifies that only the base covariates be included in the test for balance. By default, the
> powers and interactions specified by factor-variable notation in the teffects or stteffects
> model are also included in the test for balance.

nolog suppresses the display of the optimization search log.

iterate(#) sets the maximum number of iterations to # in the generalized method of moments
> estimator used to compute the test statistic.

Remarks and examples   stata.com

When the distribution of a covariate is the same for all treatment levels, the covariate is said to
be balanced. tebalance overid performs a test to see whether the covariates are balanced after
teffects or stteffects. tebalance overid can be executed after teffects ipw, teffects
aipw, teffects ipwra, stteffects ipw, or stteffects ipwra, which use the inverse-probability
weights predicted by a treatment model to account for how treatment assignment depends on observed
covariates. If the treatment model is well specified, IPW functions of the covariates from the model
are balanced.

We recommend that you read [TE] **tebalance** before proceeding; it provides an introduction
to covariate balance and an overview of the implemented methods. See [TE] **stteffects intro** for
survival-time discussion and examples.

▷ Example 1: Base covariates and interactions

This example illustrates the interpretation of the bconly option, which excludes powers and
interactions when factor variables are included in the propensity-score model.

We frequently use factor variables to include powers of, and interactions between, base covariates
in our specification of the propensity-score model. In example 1 under *Remarks and examples* in
[TE] **tebalance**, we rejected the null hypothesis of balance in a model using only base covariates
but not in the richer model that included power and interaction terms. By default, tebalance overid
tests whether the model balances the base covariates and the power-and-interaction covariates. When
option bconly is specified, tebalance overid tests whether the model balances the base covariates
only.

Using an extract from the data used by Cattaneo (2010), we use teffects ipw to estimate the effect
of a mother's smoking behavior (mbsmoke) on the birthweight of her child (bweight), controlling for
marital status (mmarried), the mother's age (mage), whether the mother had a prenatal doctor's visit
in the baby's first trimester (prenatal1), and whether this baby is the mother's first child (fbaby).
In addition to the base covariates, we include the square of mage, an interaction between mage and
mmarried, and an interaction between mage and prenatal1 in the model for the propensity score.

```
. use https://www.stata-press.com/data/r17/cattaneo2
(Excerpt from Cattaneo (2010) Journal of Econometrics 155: 138-154)

. teffects ipw (bweight) (mbsmoke mmarried mage prenatal1 fbaby
> c.mage#(c.mage i.mmarried prenatal1)), aequations

Iteration 0:   EE criterion =  9.365e-20
Iteration 1:   EE criterion =  2.612e-26
```

Treatment-effects estimation   Number of obs   =   4,642
Estimator   : inverse-probability weights
Outcome model : weighted mean
Treatment model: logit

bweight	Coefficient	Robust std. err.	z	P>|z|	[95% conf. interval]	
ATE						
mbsmoke						
(Smoker						
vs						
Nonsmoker)	-239.6875	26.43427	-9.07	0.000	-291.4977	-187.8773
POmean						
mbsmoke						
Nonsmoker	3403.638	9.56792	355.73	0.000	3384.885	3422.39
TME1						
mmarried	.8522468	.462536	1.84	0.065	-.0543072	1.758801
mage	.1742823	.0651039	2.68	0.007	.0466811	.3018836
prenatal1	.4018114	.4341762	0.93	0.355	-.4491584	1.252781
fbaby	-.4824413	.0868982	-5.55	0.000	-.6527587	-.3121239
c.mage#						
c.mage	-.002515	.0012585	-2.00	0.046	-.0049817	-.0000483
mmarried#						
c.mage						
Married	-.0787984	.0175508	-4.49	0.000	-.1131973	-.0443996
prenatal1#						
c.mage						
Yes	-.0286228	.0176391	-1.62	0.105	-.0631948	.0059492
_cons	-2.928851	.8409119	-3.48	0.000	-4.577008	-1.280694

We specified option `aequations` to see the parameter estimates for the coefficients in the propensity-score model. There are eight coefficients, five on the base covariates (`mmarried`, `mage`, `fbaby`, `prenatal1`, and `_cons`) and three on the power-and-interaction covariates (`c.mage#c.mage`, `c.mage#1.mmarried`, and `c.mage#1.prenatal1`). Below we test whether the model balances all eight covariates.

```
. tebalance overid
Iteration 0:   criterion =   .0602349
Iteration 1:   criterion =  .06172749  (backed up)
Iteration 2:   criterion =  .06428588  (backed up)
Iteration 3:   criterion =  .06489623  (backed up)
Iteration 4:   criterion =  .06527284  (backed up)
Iteration 5:   criterion =  .06643426
Iteration 6:   criterion =  .07134338
Iteration 7:   criterion =  .07638414
Iteration 8:   criterion =  .07673211
Iteration 9:   criterion =  .07681959
Iteration 10:  criterion =   .077044
Iteration 11:  criterion =  .07759547
Iteration 12:  criterion =  .07771973
Iteration 13:  criterion =   .0777271
Iteration 14:  criterion =  .07773395
Iteration 15:  criterion =  .07774839
Iteration 16:  criterion =  .07775314
Iteration 17:  criterion =  .07775324

Overidentification test for covariate balance
H0: Covariates are balanced
          chi2(8)    =   11.8612
          Prob > chi2  =    0.1575
```

We cannot reject the null hypothesis that the IPW model balanced all eight covariates.

Below we specify option bconly to test whether the IPW model balanced the five base covariates only.

```
. tebalance overid, bconly
Iteration 0:   criterion =   .1079977
Iteration 1:   criterion =  .10800825  (backed up)
Iteration 2:   criterion =  .10844177  (backed up)
Iteration 3:   criterion =  .10851228  (backed up)
Iteration 4:   criterion =  .10860856  (backed up)
Iteration 5:   criterion =  .10907494
Iteration 6:   criterion =  .11009792
Iteration 7:   criterion =  .11164102
Iteration 8:   criterion =  .11260711
Iteration 9:   criterion =  .11286467
Iteration 10:  criterion =  .11331528
Iteration 11:  criterion =  .11333981
Iteration 12:  criterion =   .1133561
Iteration 13:  criterion =  .11335696
Iteration 14:  criterion =  .11335696

Overidentification test for covariate balance
H0: Covariates are balanced
          chi2(5)    =   7.82169
          Prob > chi2  =    0.1663
```

We cannot reject the null hypothesis that the IPW model balanced the five base covariates.

Each test has a justification.

In a model-based approach, the Imai and Ratkovic (2014) test checks whether the propensity score is correctly specified. We include all eight covariates because they must all be balanced, if the propensity-score model is correctly specified.

A conditional-independence approach can be used to justify only including the base covariates in the test. In this approach, the propensity-score model need only balance the base covariates. Powers and interactions of the base covariates are included to get a propensity-score model that balances the base covariates, but balance of these higher-order terms is more than what needs to be checked.

In large samples, both tests should have nominal coverage under the null hypothesis that the propensity-score model is correctly specified. Under the alternative that the propensity-score model is misspecified, including all the covariates should yield a test with higher power.

The test that includes all the covariates is the default.

◁

Stored results

tebalance overid stores the following in r():

Scalars
r(p)	*p*-value
r(df)	overidentifying constraints, test degrees of freedom
r(chi2)	χ^2 statistic

References

Cattaneo, M. D. 2010. Efficient semiparametric estimation of multi-valued treatment effects under ignorability. *Journal of Econometrics* 155: 138–154. https://doi.org/10.1016/j.jeconom.2009.09.023.

Imai, K., and M. Ratkovic. 2014. Covariate balancing propensity score. *Journal of the Royal Statistical Society, Series B* 76: 243–263. https://doi.org/10.1111/rssb.12027.

Also see

[TE] **stteffects intro** — Introduction to treatment effects for observational survival-time data

[TE] **tebalance** — Check balance after teffects or stteffects estimation

[TE] **teffects aipw** — Augmented inverse-probability weighting

[TE] **teffects ipw** — Inverse-probability weighting

[TE] **teffects ipwra** — Inverse-probability-weighted regression adjustment

[TE] **teoverlap** — Overlap plots