

Title

rdplot — Data-Driven Regression Discontinuity Plots.

Syntax

rdplot depvar indepvar [if] [in] [, c(#) nbins(# #) binselect(binmethod) scale(#
 #) support(# #) p(#) h(# #) kernel(kernelfn) weights(weightsvar) covs(covars)
 covs_eval(covars_eval) covs_drop(covsdropoption) ci(cilevel) shade
 graph_options(gphopts) hide genvars]

Description

rdplot implements several data-driven Regression Discontinuity (RD) plots, using
 either evenly-spaced or quantile-spaced partitioning. Two type of RD plots are
 constructed: (i) RD plots with binned sample means tracing out the underlying
 regression function, and (ii) RD plots with binned sample means mimicking the
 underlying variability of the data. For technical and methodological details
 see Calonico, Cattaneo and Titiunik (2015a).

Companion commands are: rdrobust for point estimation and inference procedures, and rdbwselect for data-driven bandwidth selection.

A detailed introduction to this command is given in <u>Calonico</u>, <u>Cattaneo and Titiunik (2014)</u>, and <u>Calonico</u>, <u>Cattaneo</u>, <u>Farrell and Titiunik (2017)</u>. A companion R package is also described in <u>Calonico</u>, <u>Cattaneo and Titiunik (2015b)</u>.

Related Stata and R packages useful for inference in RD designs are described in the following website:

https://sites.google.com/site/rdpackages/

Options

Estimand

c(#) specifies the RD cutoff in indepvar. Default is c(0).

Bin Selection

nbins(# #) specifies the number of bins used to the left of the cutoff, denoted J-, and to the right of the cutoff, denoted J+, respectively. If not specified, J+ and J- are estimated using the method and options chosen below.

binselect(binmethod) specifies the data-driven procedure to select the number of bins. This option is available only if J- and J+ are not set manually using **nbins(.)**. Options are:

nbins(.). Options are:

es IMSE-optimal evenly-spaced method using spacings estimators.

espr IMSE-optimal evenly-spaced method using polynomial regression.
esmv mimicking variance evenly-spaced method using spacings estimators.
esmvpr mimicking variance evenly-spaced method using polynomial regression.
qs IMSE-optimal quantile-spaced method using spacings estimators.

qs imsE-optimal quantile-spaced method using spacings estimators.
qspr IMSE-optimal quantile-spaced method using polynomial regression.
qsmv mimicking variance quantile-spaced method using spacings estimators.

qsmv mimicking variance quantile-spaced method using spacings estimators. **qsmvpr** mimicking variance quantile-spaced method using polynomial regression. Default is **binselect(esmv)**.

Note: procedures involving spacing estimators are not invariant to rearrangements of depvar when there are repeated values (i.e., mass points in the running variable).

scale(# #) specifies multiplicative factors, denoted s- and s+, respectively, to
 adjust the number of bins selected. Specifically, the number of bins used for
 the treatment and control groups will be ceil(s- * J-) and ceil(s+ * J+),
 where J- and J+ denote the optimal numbers of bins originally computed for
 each group. Default is scale(1 1).

support(# #) sets an optional extended support of the running variable to be used
 in the construction of the bins. Default is the sample range.

→ Polynomial Fit

- p(#) specifies the order of the (global) polynomial fit used to approximate the population conditional expectation functions for control and treated units. Default is p(4).
- h(# #) specifies the bandwidth used to construct the (global) polynomial fits
 given the kernel choice kernel(.). If not specified, the bandwidths are
 chosen to span the full support of the data. If two bandwidths are specified,
 the first bandwidth is used for the data below the cutoff and the second
 bandwidth is used for the data above the cutoff.
- kernel(kernelfn) specifies the kernel function used to construct the
 local-polynomial estimator(s). Options are: triangular, epanechnikov, and
 uniform. Default is kernel(uniform) (i.e., equal/no weighting to all
 observations on the support of the kernel).
- weights(weightsvar) is the variable used for optional weighting of the estimation
 procedure. The unit-specific weights multiply the kernel function.
- covs(covars) additional covariates used to construct the local-polynomial
 estimator(s).
- covs_eval(covars_eval) sets the evaluation points for the additional covariates,
 when included in the estimation. Options are: 0 (default) and mean.
- covs_drop(covsdropoption) specifies options to assess collinearity in covariates
 to be used for estimation and inference. Option on drops collinear additional
 covariates (default choice). Option off only checks collinear additional
 covariates but does not drop them.

Plot Options

 ${\tt ci}\ (cilevel)$ graphical option to display confidence intervals of level cilevel for each bin.

shade graphical option to replace confidence intervals with shaded areas.

graph_options(gphopts) graphical options to be passed on to the underlying graph command.

hide omits the RD plot.

Generate Variables

genvars generates new variables storing the following results.

rdplot_id unique bin ID for each observation. Negative natural numbers are
 assigned to observations to the left of the cutoff, and positive natural
 numbers are assigned to observations to the right of the cutoff.

rdplot_N number of observations in the corresponding bin for each observation.

rdplot_min_bin lower end value of the bin for each observation.

rdplot_max_bin upper end value of the bin for each observation.

rdplot_mean_bin middle point of the corresponding bin for each observation.
rdplot_mean_x sample mean of the running variable within the corresponding bin for each observation.

rdplot_mean_y sample mean of the outcome variable within the corresponding bin
 for each observation.

 ${\tt rdplot_se_y}$ standard deviation of the mean of the outcome variable within the corresponding bin for each observation.

rdplot_ci_1 lower end value of the confidence interval for the sample mean of the outcome variable within the corresponding bin for each observation.

 $\begin{tabular}{ll} \textbf{rdplot_hat_y} & predicted value of the outcome variable given by the global \\ polynomial estimator. \end{tabular}$

Example: Cattaneo, Frandsen and Titiunik (2015) Incumbency Data

```
Setup
. use rdrobust_senate.dta

Basic specification with title
. rdplot vote margin, graph_options(title(RD Plot))

Quadratic global polynomial with confidence bands
. rdplot vote margin, p(2) ci(95) shade
```

Stored results

rdplot stores the following in e():

```
Scalars
  e(N_1)
                      original number of observations to the left of the cutoff
  e(N_r)
                      original number of observations to the right of the cutoff
  e(c)
                      cutoff value
  e(J_star_1)
                      selected number of bins to the left of the cutoff
                      selected number of bins to the right of the cutoff
  e(J_star_r)
Macros
  e(binselect)
                    method used to compute the optimal number of bins
Matrices
  e(coef_1)
                     coefficients of the p-th order polynomial estimated to the
                       left of the cutoff
  e(coef_r)
                      coefficients of the p-th order polynomial estimated to the
                       right of the cutoff
```

References

- Calonico, S., M. D. Cattaneo, M. H. Farrell, and R. Titiunik. 2017. rdrobust:
 Stata Journal, 17(2): 372-404.
- Calonico, S., M. D. Cattaneo, and R. Titiunik. 2014b. <u>Robust Data-Driven</u>
 <u>Inference in the Regression-Discontinuity Design</u>. *Stata Journal* 14(4): 909-946.
- Calonico, S., M. D. Cattaneo, and R. Titiunik. 2015a. <u>Optimal Data-Driven Regression Discontinuity Plots</u>. Journal of the American Statistical Association 110(512): 1753-1769.
- Calonico, S., M. D. Cattaneo, and R. Titiunik. 2015b. <u>rdrobust: An R Package for Robust Nonparametric Inference in Regression-Discontinuity Designs</u>. *R Journal* 7(1): 38-51.
- Cattaneo, M. D., B. Frandsen, and R. Titiunik. 2015. <u>Randomization Inference in the Regression Discontinuity Design: An Application to Party Advantages in the U.S. Senate</u>. *Journal of Causal Inference* 3(1): 1-24.

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