

# **Title**

lpbwselect — Bandwidth Selection Procedures for Local Polynomial Regression
 Estimation and Inference.

### Syntax

lpbwselect yvar xvar [if] [in] [, eval(gridvar) neval(#) deriv(#) p(#) rho(#)
 kernel(kernelfn) bwselect(bwmethod) bwcheck(#) imsegrid(#) vce(vcetype
 [vceopt]) bwregul(#) separator(#) interior ]

# Description

- lpbwselect implements bandwidth selectors for local polynomial regression point
   estimators and inference procedures developed in <u>Calonico, Cattaneo and
   Farrell (2018)</u>. See also <u>Calonico, Cattaneo and Farrell (2020)</u> for related
   optimality results. It also implements other bandwidth selectors available in
   the literature. See Wand and Jones (1995) and Fan and Gijbels (1996) for
   background references.
- A detailed introduction to this command is given in <u>Calonico</u>, <u>Cattaneo and Farrell</u> (2019).
- Companion command is:  $\underline{lprobust}$  for local polynomial point estimation and inference procedures.
- Related Stata and R packages useful for empirical analysis are described in the following website:

https://nppackages.github.io/

# Options

- **eval**(gridvar) specifies the grid of evaluation points for xvar. By default it uses 30 equally spaced points over to support of xvar.
- neval(#) specifies the number of evaluation points to estimate the regression
  functions. Default is 30 evaluation points.
- $\operatorname{deriv}(\#)$  specifies the order of the derivative of the regression functions to be estimated. Default is  $\operatorname{deriv}(0)$ .
- p(#) specifies the order of the local polynomial used to construct the point estimator. Default is p(1) (local linear regression).
- **rho**(#) specifies the value of *rho*, so that the bias bandwidth b equals b=h/rho. Default is **rho**(1) if h is specified but b is not.
- kernel(kernelfn) specifies the kernel function used to construct the
   local-polynomial estimator(s). Options are: triangular, epanechnikov, uniform
   and gaussian. Default is kernel(epanechnikov).
- bwselect(bwmethod) bandwidth selection procedure to be used. Options are:
   mse-dpi second-generation DPI implementation of MSE-optimal bandwidth. Default
   choice.

mse-rot ROT implementation of MSE-optimal bandwidth.

imse-dpi second-generation DPI implementation of IMSE-optimal bandwidth.

imse-rot ROT implementation of IMSE-optimal bandwidth.

ce-dpi second generation DPI implementation of CE-optimal bandwidth.

ce-rot ROT implementation of CE-optimal bandwidth.

- Note: MSE = Mean Square Error; IMSE = Integrated Mean Squared Error; CE = Coverage Error; DPI = Direct Plug-in; ROT = Rule-of-Thumb.

  Default is **bwselect**(mse-dpi). For details on implementation see <u>Calonico</u>,
  - Default is **bwselect(**mse-dpi**).** For details on implementation see <u>Calonico</u>, <u>Cattaneo and Farrrell (2019)</u>.
- bwcheck(#) specifies an optional positive integer so that the selected bandwidth
   is enlarged to have at least # effective observations available for each
   evaluation point.

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imsegrid(#) number of evaluations points used to compute the IMSE bandwidth
        selector. Default is 30 points.
    vce(vcetype [vceopt1]) specifies the procedure used to compute the
        variance-covariance matrix estimator. Options are:
        vce(nn [nnmatch]) for heteroskedasticity-robust nearest neighbor variance
            estimator with nnmatch indicating the minimum number of neighbors to be
            used.
        vce(hc0) for heteroskedasticity-robust plug-in residuals variance estimator
            without weights.
        vce(hc1) for heteroskedasticity-robust plug-in residuals variance estimator
            with hcl weights.
        \mathbf{vce} (hc2) for heteroskedasticity-robust plug-in residuals variance estimator
            with hc2 weights.
        vce(hc3) for heteroskedasticity-robust plug-in residuals variance estimator
            with hc3 weights.
        vce(nncluster clustervar [nnmatch]) for cluster-robust nearest neighbor
variance estimation using with clustervar indicating the cluster ID
            variable and nnmatch matches indicating the minimum number of neighbors to
        vce(cluster clustervar) for cluster-robust plug-in residuals variance
            estimation with degrees-of-freedom weights and clustervar indicating the
            cluster ID variable.
        Default is vce(nn 3).
    bwregul(#) specifies scaling factor for the regularization term added to the
        denominator of the bandwidth selectors. Setting bwregul(0) removes the
        regularization term from the bandwidth selectors. Default is bwrequl(1).
    separator(#) draws separator line after every # variables; default is
        separator(5).
Example:
    Setup
        . webuse motorcycle
    Second-generation DPI implementation of MSE-optimal bandwidth
        . lpbwselect accel time
Saved results
```

lpbwselect saves the following in e():

```
Scalars
 e (N)
                      original number of observations
                      order of the polynomial used for estimation of the
  e (p)
                        regression function
Macros
  e (varname)
                     name of variable
  e(clustvar)
                      name of cluster variable
  e(bwselect)
                      bandwidth selection choice
                     kernel choice
  e(kernel)
  e (vce)
                     vce choice
Matrices
  e (bws)
                     estimation result
```

# References

Calonico, S., M. D. Cattaneo, and M. H. Farrell. 2018. On the Effect of Bias Estimation on Coverage Accuracy in Nonparametric Inference. Journal of the American Statistical Association, 113 (522): 767-779.

- Calonico, S., M. D. Cattaneo, and M. H. Farrell. 2019. <a href="mailto:nprobust: Nonparametric Kernel-Based Estimation and Robust Bias-Corrected Inference">nprobust: Nonparametric Kernel-Based Estimation and Robust Bias-Corrected Inference</a>. Journal of Statistical Software, 91(8): 1-33. <a href="mailto:doi:10.18637/jss.v091.i08">doi: 10.18637/jss.v091.i08</a>.
- Calonico, S., M. D. Cattaneo, and M. H. Farrell. 2020. <u>Coverage Error Optimal Confidence Intervals for Local Polynomial Regression</u>, working paper.
- Fan, J., and Gijbels, I. 1996. Local Polynomial Modelling and Its Applications, London: Chapman and Hall.
- Wand, M., and Jones, M. 1995. Kernel Smoothing, Florida: Chapman & Hall/CRC.

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