

# Journal of Statistical Software

 $MMMMMM\ YYYY,\ Volume\ VV,\ Issue\ II.$ 

http://www.jstatsoft.org/

# rddtools: tools for Regression Discontinuity Design in R

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#### Abstract

The rddtools package implements functions for handling Regression Discontinuity Design in R.

Keywords: RDD, Regression, Discontinuity, Design, R.

### 1. Introduction

The rddtools package attempts to provide a unified approach to the application of Regression Discontinuity Design (RDD) in R.

# 2. Design

A unified framework for RDD is implemented through the rdd\_data class which inherits from the R base package's data.frame class. This functionality is made accessible through the associated rdd\_data() function, as well as the following associated methods.

- [.rdd\_data() / subset.rdd\_data()
- summary.rdd\_data()
- plot.rdd\_data()

The package is designed to leveredge of existing implementations of **Regression Discontinuity Design** in R, such as the rdd (Dimmery 2013) and KernSmooth (M. Wand 2015) packages. Furthermore, general algorithms such as non-parametric regression from the np package (Hayfield and Racine 2008) is made accessible for RDD through the rdd\_data framework.

In addition to this, it implements several tools for RDD analysis that were previously unavailable.

#### 2.1. Bandwidth Selection

Two new methods for Bandwidth selection are included.

- MSE-RDD bandwidth procedure of (G. Imbens and Kalyanaraman 2012): rdd\_bw\_ik()
- MSE global bandwidth procedure of (Ruppert, Sheather, and Wand 1995): rdd\_bw\_rsw()

#### 2.2. Estimation

RDD parametric estimation: rdd\_reg\_lm() This includes specifying the polynomial order, including covariates with various specifications as advocated in (G. W. Imbens and Lemieux 2008).

RDD local non-parametric estimation: rdd\_reg\_np(). Can also include covariates, and allows different types of inference (fully non-parametric, or parametric approximation).

RDD generalised estimation: allows to use custom estimating functions to get the RDD coefficient. Could allow for example a probit RDD, or quantile regression.

#### 2.3. Post-Estimation

A collection of Post-Estimation tools allow the robustness of the estimation results to be verified.

Various tools, to obtain predictions at given covariate values ( rdd\_pred() ), or to convert to other classes, to lm ( as.lm() ), or to the package np ( as.npreg() ).

Function to do inference with clustered data: clusterInf() either using a cluster covariance matrix (vcovCluster()) or by a degrees of freedom correction (as in (Cameron, Gelbach, and Miller 2008)).

Contains functions to replicate the Monte-Carlo simulations of [Imbens and Kalyanaraman 2012]: gen\_mc\_ik()

#### 2.4. Regression Sensitivity Analysis

Plot the sensitivity of the coefficient with respect to the bandwith: plotSensi()

Placebo plot using different cutpoints: plotPlacebo()

#### 2.5. Design sensitivity analysis

McCrary test of manipulation of the forcing variable: wrapper dens\_test() to the function DCdensity() from package rdd.

Test of equal means of covariates: covarTest\_mean()

Test of equal density of covariates: covarTest\_dens()

#### 3. Data

A collection of typical data sets is included in the package.

- Initiative Nationale pour le Développement Humain (Arcand, Rieger, and Nguyen 2015): indh
- Voting in the U.S. House of Representatives (Lee 2008): house
- STAR dataset (Angrist and Pischke 2008): STAR\_MHE

Both data sets is made available as a data.frame. Using the previously discuss rdd\_data() function we can transform a data.frame to an object of class rdd\_data, which inherits from data.frame.

Here we can the data from the Initiative Nationale pour le Développement Humain (INDH), a development project in Morocco. The data is included with the package under the name indh.

```
[1] "indh"
```

Now that we have loading the data we can briefly inspect the structure of the data.

```
str(indh)
```

```
'data.frame': 720 obs. of 2 variables:

$ choice_pg: int 0 1 1 1 1 1 0 1 0 0 ...

$ poverty : num 30.1 30.1 30.1 30.1 30.1 ...
```

The indh object is a data.frame containing 720 observations (representing individuals) of two variables:

- choice\_pg
- poverty

The variable of interest is choice\_pg, which represent the decision to contibute to a public good or not. The observations are individuals choosing to contribute or not, these individuals are clustered by the variable commune which is the municiple structure at which funding was distributed as part of the INDH project. The forcing variable is poverty which represents the number of households in a commune living below the poverty threshold. As part of the INDH, commune with a proportion of household below the poverty threshold greater than 30% were allowed to distribute the funding using a Community Driven Development scheme. The cutoff point for our analysis is therefore 30.

We can now transform the data.frame to a special rdd\_data-class object, inhereting from the data.frame class using the rdd\_data() function.

- attr(\*, "type")= chr "Sharp"

The rdd\_data() can be used using the data argument, in which case the function will look for the values o y and x in this argument (before looking in the .GlobalEnv), if this argument is NULL, only the .GlobalEnv will be scanned. Additional exogenous variables can be included using the covar argument.

The structure is similar to the original data.frame object, but contains some additional information.

```
str(rdd_dat_indh)

Classes 'rdd_data' and 'data.frame': 720 obs. of 2 variables:
$ x: num  30.1 30.1 30.1 30.1 30.1 ...
$ y: int  0 1 1 1 1 1 0 1 0 0 ...
- attr(*, "hasCovar")= logi FALSE
- attr(*, "labels")= list()
- attr(*, "cutpoint")= num 30
```

The rdd\_data object has the classes data.frame and rdd\_data. It contains two variables, y the explanandum or dependent variable and x the explanans or driving variable, which is also our discontinuous variable. Related to the discontinuous variable is the attribute called cutpoint, which describes where in the domain of x the discontinuity occurs. The hasCover attribute indicates if additional exogenous variables have been included using the cover argument to the rdd\_data() function.

# 4. Analysis

In order to best understand our data, we start with an exploratory data analysis using tables. . .

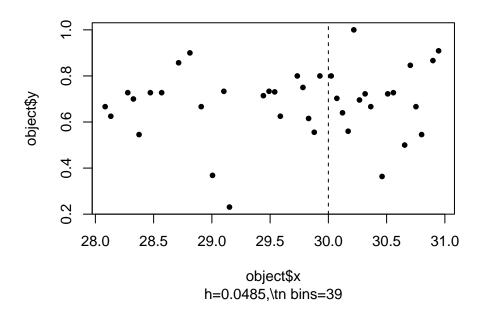
```
summary(rdd_dat_indh)

### rdd_data object ###

Cutpoint: 30
Sample size:
    -Full : 720
    -Left : 362
    -Right: 358
Covariates: no

...and plots.

plot(rdd_dat_indh)
```



We can now continue with a standard Regression Discontinuity Design estimation.

```
reg_para <- rdd_reg_lm(rdd_dat_indh, order=4)
print(reg_para) # uses print.rdd_data</pre>
```

```
### RDD regression: parametric ###
```

Polynomial order: 4 Slopes: separate

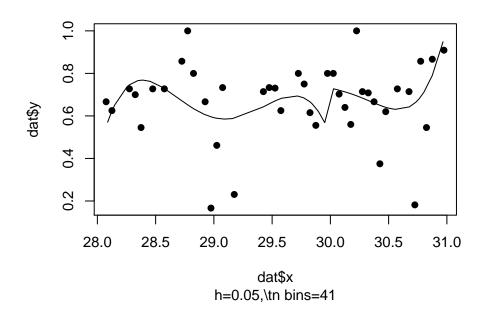
Number of obs: 720 (left: 362, right: 358)

#### Coefficient:

Estimate Std. Error t value Pr(>|t|)
D 0.22547 0.17696 1.2741 0.203

and visualising this estimation.

```
plot(reg_para)
```



In addition to the parametric estimation, we can also perform a non-parametric estimation.

```
bw_ik <- rdd_bw_ik(rdd_dat_indh)
reg_nonpara <- rdd_reg_np(rdd_object=rdd_dat_indh, bw=bw_ik)
reg_nonpara</pre>
```

```
### RDD regression: nonparametric local linear###
```

Bandwidth: 0.790526

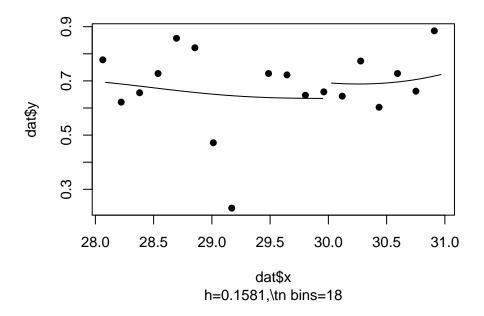
Number of obs: 460 (left: 139, right: 321)

#### Coefficient:

Estimate Std. Error z value Pr(>|z|)D 0.144775 0.095606 1.5143 0.13

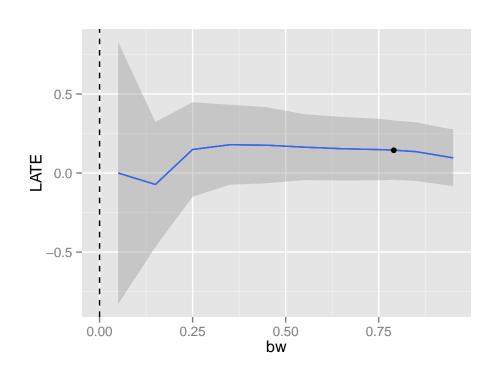
and visualising the non-parametric estimation.

plot(reg\_nonpara)



Sensitity tests.

plotSensi(reg\_nonpara, from=0.05, to=1, by=0.1)



# 5. Conclusion and Discussion

The package rddtools provides a unified framework for working with Regression Discontinuity Data in R. Functionality already available is several existing packages, such as rdd and KernSmooth can now easilty be utlised using the rdd\_data framework, as well as several linking functions.

In addition to this, new tools and algorithms are also implement, as well as various postestimation robustness checks.

Future packages implementing further RDD functionality can easily leverage the rdd\_data framework, which allows users to quickly access new functionality through a familiar API.

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Submitted: 2015-07-25

Accepted: yyyy-mm-dd

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