

Multidimensional Regression Discontinuity and Regression Kink Designs with Difference-in-Differences

Rafael P. Ribas

University of Amsterdam

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Motivation

- Regression Discontinuity (RD) designs have been broadly applied.
- However, non-parametric estimation is restricted to simple specifications.
 - I.e., cross-sectional data with one running variable.
- Thus some papers still use parametric polynomial forms and/or arbitrary bandwidths. For instance,
 - Dell (2010, *Econometrica*) estimates a two-dimensional RD.
 - Grembi et al. (2016, *AEJ:AE*) estimates Difference-in-Discontinuities.
- The goal is to create a program (such as `rdrobust`) that accommodates more flexible specifications.

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Overview

- The `ddrd` package is built upon `rdrobust` package, including the following options:
 - 1 Difference-in-Discontinuities (DiD) and Difference-in-Kinks (DiK)
 - 2 Multiple running variables
 - 3 Analytic weights (`aweight`)
 - 4 Control variables
 - 5 Heterogeneous effect through linear interaction (in progress).
- All options are taken into account when computing the optimal bandwidth, using `ddbwsel`.
 - The estimator changes, so does the procedure.

Difference-in-Discontinuity/Kink, Notation

- Let $\mu_t(x) = \mathbb{E}[Y|X = x, t]$ and $\mu_t^{(v)}(x) = \frac{\partial^v E[Y|X=x,t]}{(\partial x)^v}$.
- Then the conventional sharp RD/RK estimand is:

$$\tau_{v,t} = \lim_{x \rightarrow 0^+} \mu_t^{(v)}(x) - \lim_{x \rightarrow 0^-} \mu_t^{(v)}(x) = \mu_{t+}^{(v)} - \mu_{t-}^{(v)}$$

- The DiD/DiK estimand is:

$$\Delta\tau_v = \mu_{1+}^{(v)} - \mu_{1-}^{(v)} - [\mu_{0+}^{(v)} - \mu_{0-}^{(v)}]$$

Optimal Bandwidth, h^*

- Two methods based on the mean square error (MSE):

$$h_{MSE}^* = \left[C(K) \frac{\text{Var}(\hat{\tau}_v)}{\text{Bias}(\hat{\tau}_v)^2} \right]^{\frac{1}{5}} n^{-\frac{1}{5}}$$

- Imbens and Kalyanaraman (2012), IK.
- Calonico, Cattaneo and Titiunik (2014), CCT.
- They differ in the way $\text{Var}(\hat{\tau}_v)$ and $\text{Bias}(\hat{\tau}_v)$ are estimated.
- For DiD/DiK, the trick is to replace $\hat{\tau}_v$ by $\Delta\hat{\tau}_v$.
 - That's what `ddbwsel` does.
- While `ddrd` calculates the robust, bias-corrected confidence intervals for $\Delta\hat{\tau}_v$, as proposed by CCT.

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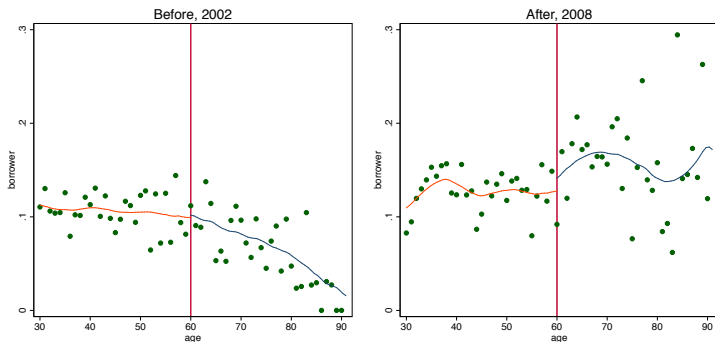
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Application: Retirement and Payroll Credit in Brazil

- In 2003, Brazil passed a legislation regulating payroll lending.
 - Loans for which interests are deducted from payroll check (Coelho et al., 2012).
 - It represented a “kink” in loans to pensioners.

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Application: Retirement and Payroll Credit in Brazil

- Optimal bandwidth for Difference-in-Kink at age 60:

```
. ddbwsel borrower aged [aw=weight], time(time) c(60) deriv(1) all
Computing CCT bandwidth selector.
Computing IK bandwidth selector.
```

Bandwidth estimators for local polynomial regression

Cutoff c = 60			Left of c	Right of c		
-----+-----					Number of obs =	53757
Number of obs, t = 0	20836	4484			NN matches =	3
Number of obs, t = 1	22609	5828			Kernel type =	Triangular
Order loc. poly. (p)	2	2				
Order bias (q)	3	3				
Range of aged, t = 0	29.996	29.999				
Range of aged, t = 1	29.996	29.996				

Method	h	b	rho			
-----+-----						
CCT	12.45718	18.73484	.6649206			
IK	14.46675	11.01818	1.312989			

Application: Retirement and Payroll Credit in Brazil

- ddrd output:

```
. ddrd borrower aged [aw=weight], time(time) c(60) deriv(1) b('b') h('h')
Preparing data.
Calculating predicted outcome per sample.
Estimation completed.
```

Estimates using local polynomial regression. Derivative of order 1.

Cutoff c = 60	Left of c	Right of c		Number of obs =	27093
-----+-----				NN matches =	3
Number of obs, t = 0	6117	3081		BW type =	Manual
Number of obs, t = 1	7319	4001		Kernel type =	Triangular
Order loc. poly. (p)	2	2			
Order bias (q)	3	3			
BW loc. poly. (h)	12.457	12.457			
BW bias (b)	18.735	18.735			
rho (h/b)	0.665	0.665			

Outcome: borrower. Running Variable: aged.

Method	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
-----+-----					
Conventional	.0229	.0221	1.0362	0.300	-.020417 .066218
Robust	.0271	.03123	0.8680	0.385	-.034098 .088303
-----+-----					

Difference-in-Kink

- What if there is no cutoff and **aged** is a continuous treatment?
- Shift in level represents the *first* difference, while change in the slope represents the *second* difference.
 - Difference-in-Difference with continuous treatment.

Difference-in-Kink

Estimating changes in the first derivative at any part of the function:

```
. ddrd borrower aged [aw=weight], time(time) c(60) deriv(1) nocut
Preparing data.
Computing bandwidth selectors.
Calculating predicted outcome per sample.
Estimation completed.
```

Estimates using local polynomial regression. Derivative of order 1.

Reference c = 60	Time 0	Time 1	Number of obs =	53757
-----+-----			NN matches =	3
Number of obs	8433	10395	BW type =	CCT
Order loc. poly. (p)	2	2	Kernel type =	Triangular
Order bias (q)	3	3		
BW loc. poly. (h)	11.489	11.489		
BW bias (b)	16.813	16.813		
rho (h/b)	0.683	0.683		

Outcome: borrower. Running Variable: aged.

Method	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
-----+-----					
Conventional	.00473	.00161	2.9473	0.003	.001585 .007879
Robust	.00528	.0022	2.3988	0.016	.000966 .009598
-----+-----					

Multidimensional RD, Notation

- Suppose X has k dimensions, i.e. $X = \{x_1, \dots, x_k\}$.
- Cutoff doesn't have to be unique.
- Let $\mathbf{c} = \{(c_{11}, \dots, c_{n1}), \dots, (c_{1L}, \dots, c_{nL})\}$ be the cutoff hyperplane.
 - It separates treated and control.
- z_i indicates whether i is “intended for treatment” (in the treated set) or not (in the control set).
- **Trick:** pick one point in \mathbf{c} , say $\mathbf{c}_l = (c_{1l}, \dots, c_{nl})$, and reduce X to one dimension by calculating the distance $d(\mathbf{x}_i, \mathbf{c}_l)$ for every i .
- The new running variable is:

$$r_i = (2 \cdot z_i - 1) \cdot d(\mathbf{x}_i, \mathbf{c}_l).$$

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Multidimensional RD

- With one running variable, r , I can apply the previous methods.
- `ddrd` includes the following distance functions:
 - Manhattan (L1)
 - Euclidean (L2)
 - Minkowski (Lp)
 - Mahalanobis
 - Latitude-Longitude
- **Caveat:** If cutoff isn't unique, $\hat{\tau}_v$, $\Delta\hat{\tau}_v$, and h^* depend on the chosen cutoff point.
 - The effect can be heterogeneous.
- **Solution:** Average effect from several different cutoffs.
 - Correlation between cutoffs should be taken into account (in progress).

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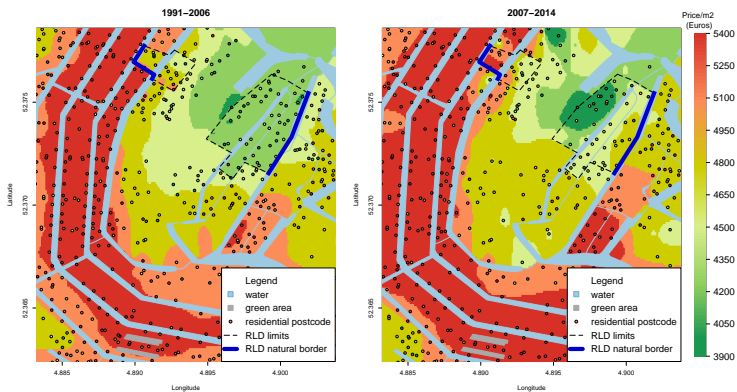
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Application: The Effect of Prostitution on House Prices

- In Amsterdam, the canals are like natural borders of the red light district (RLD).



Application: The Effect of Prostitution on House Prices

- ddrd output:

```
. ddrd lprice Lat Lon if time==0, itt(rldA) c(52.374611 4.901397) dfunction(Latlong)
Computing Latlong distance
Preparing data.
Computing bandwidth selectors.
Calculating predicted outcome per sample.
Estimation completed.
```

Estimates using local polynomial regression.

Cutoff c = 0	Left of c	Right of c	Number of obs =	53174
-----+-----			NN matches =	3
Number of obs	99	124	BW type =	CCT
Order loc. poly. (p)	1	1	Kernel type =	Triangular
Order bias (q)	2	2		
BW loc. poly. (h)	7.445	7.445		
BW bias (b)	11.258	11.258		
rho (h/b)	0.661	0.661		

Outcome: lprice. Running Variable: Lat Lon.

Method	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
-----+-----					
Conventional	-.27857	.06379	-4.3669	0.000	-.403605 -.153544
Robust	-.30377	.09626	-3.1557	0.002	-.492442 -.115104
-----+-----					

Application: The Effect of Prostitution on House Prices

● ddrd output, with DiD:

```
. ddrd lprice Lat Lon, itt(rldA) time(time) c(52.374611 4.901397) dfunction(Latlong)
Computing Latlong distance
Preparing data.
Computing bandwidth selectors.
Calculating predicted outcome per sample.
Estimation completed.
```

Estimates using local polynomial regression.

Cutoff c = 0	Left of c	Right of c		
-----+-----			Number of obs =	49055
Number of obs, t = 0	86	90	NN matches =	3
Number of obs, t = 1	60	47	BW type =	CCT
Order loc. poly. (p)	1	1	Kernel type =	Triangular
Order bias (q)	2	2		
BW loc. poly. (h)	6.937	6.937		
BW bias (b)	11.963	11.963		
rho (h/b)	0.580	0.580		

Outcome: lprice. Running Variable: Lat Lon.

Method	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
-----+-----					
Conventional	.3801	.1498	2.5374	0.011	.086495 .673705
Robust	.51914	.21802	2.3811	0.017	.091824 .946453
-----+-----					

Control Variables

- In the previous example, we are interested in residents' willingness to pay for the location.
- However, house prices comprise both quality and location.
 - And house quality is also affected by amenities.
- Solution is to control for house characteristics.
- How?
- I apply the Frisch-Waugh theorem in 3 steps (McMillen and Redfearn, 2010):
 - Regress variables (x) and y on the running variable (r).
 - Estimate the coefficient vector β by regressing residuals of y on residuals of x .
 - Regress $(y - \hat{\beta}'x)$ on the running variable (r).

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Application: The Effect of Prostitution on House Prices

- ddrd output, with control variables:

```
. ddrd lprice Lat Lon if time==0, itt(rldA) c(52.374611 4.901397) dfunction(Latlong) control(siz
> e date1-date4 monumnt poorcnd luxury rooms floors kitchen bath centhet balcony attic terrace l
> ift garage garden)
```

(...)

Estimates using local polynomial regression.

Cutoff c = 0	Left of c	Right of c	Number of obs =	72434
-----+-----			NN matches =	3
Number of obs	117	135	BW type =	Manual
Order loc. poly. (p)	1	1	Kernel type =	Triangular
Order bias (q)	2	2		
BW loc. poly. (h)	7.445	7.445		
BW bias (b)	11.258	11.258		
rho (h/b)	0.661	0.661		

Outcome: lprice. Running Variable: Lat Lon.

Method	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
-----+-----					
Conventional	-.50715	.22619	-2.2422	0.025	-.950466 -.063836
Robust	-.61673	.36225	-1.7025	0.089	-1.32674 .093267
-----+-----					

```
Control variables: size date1 date2 date3 date4 monumnt poorcnd luxury rooms floors kitchen bath
> centhet balcony attic terrace lift garage garden.
```