

Estimating Compulsory Schooling Impacts on Labour Market Outcomes in Mexico

Fuzzy Regression Discontinuity Design (RDD) with parametric and non-parametric analyses

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Outline

- Applied economics
- Fuzzy RDD
- RDD validity
- Non-parametric analysis
- Parametric analysis
- Conclusions

Analysis of educational policies on **earnings**

- Long debate whether schooling is linked to long-run labour market outcomes
- Measuring the sole impact of education is challenging
- **Endogeneity** between schooling and labour market outcomes: education and earnings are jointly determined
- **Imperfect compliance** with the policy: some factors could affect the exposure to the policy
 - a people not treated that should be treated
 - b people should not be treated and are actually treated

Robust methodology for measuring impact evaluation or the effectiveness of different policies

Fuzzy Regression Discontinuity Design (RDD)

Fuzzy RDD in spirit of Grenet (2013) and Aydemir and Kirdar (2017)

- Non-parametric analysis
- Parametric analysis

Shed light of the **impacts of the 1993 compulsory schooling** on labour market outcomes in Mexico: earnings and employment sectoral choices

- Raise **compulsory school-leaving age from 12 to 15 years**
- Encourage children to **accumulate human capital**

The fuzziness addresses **imperfect compliance** with the policy

- Use the random assignment of the exposure to the policy

Fuzzy Regression Discontinuity Design (RDD)

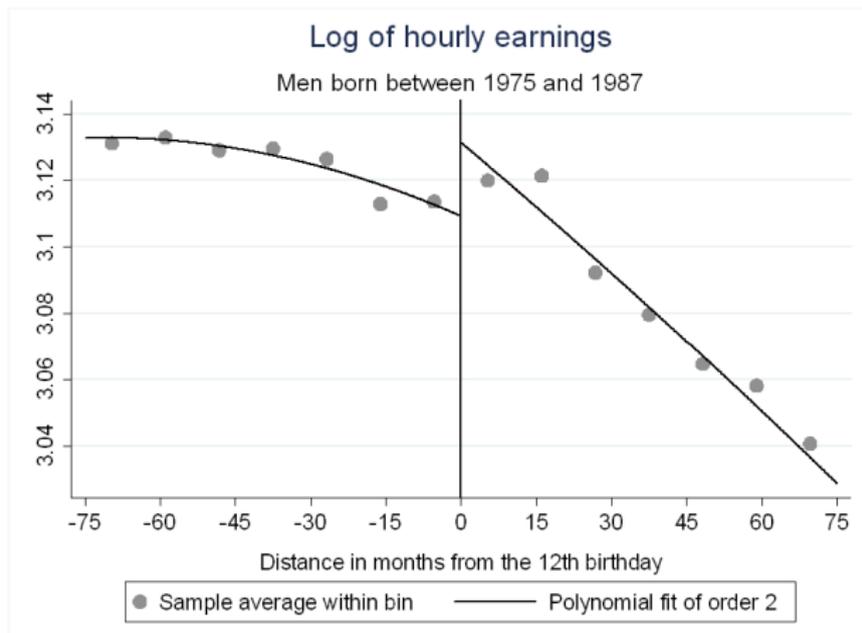
- Age cohort discontinuities measured in **months of birth**
- **Exogenous extra-compulsory schooling** faced by different birth cohorts
- Compare people **treated with untreated** by the policy
- **Running variable** is the age in months of birth from the cohort born in September 1981

$$Treatment_i \begin{cases} 1, & \text{if cohort born} \geq \text{September 1981} \\ 0, & \text{if cohort born} < \text{September 1981} \end{cases}$$

RDD validity - Discontinuity plots



RDD validity - Discontinuity plots



RDD validity -Discontinuity plots

rdplot implements several data-driven regression-discontinuity (RD) plots, using either evenly spaced or quantile-spaced partitioning

```
rdplot depvar runvar [if] [in] [, c(cutoff) p(pvalue) binselect(binmethod) graph_options(gphopts)]
```

where *depvar* is the dependent variable, and *runvar* is the running variable (also known as the score or forcing variable).

c(cutoff) specifies the RD cutoff. The default is *c(0)*.

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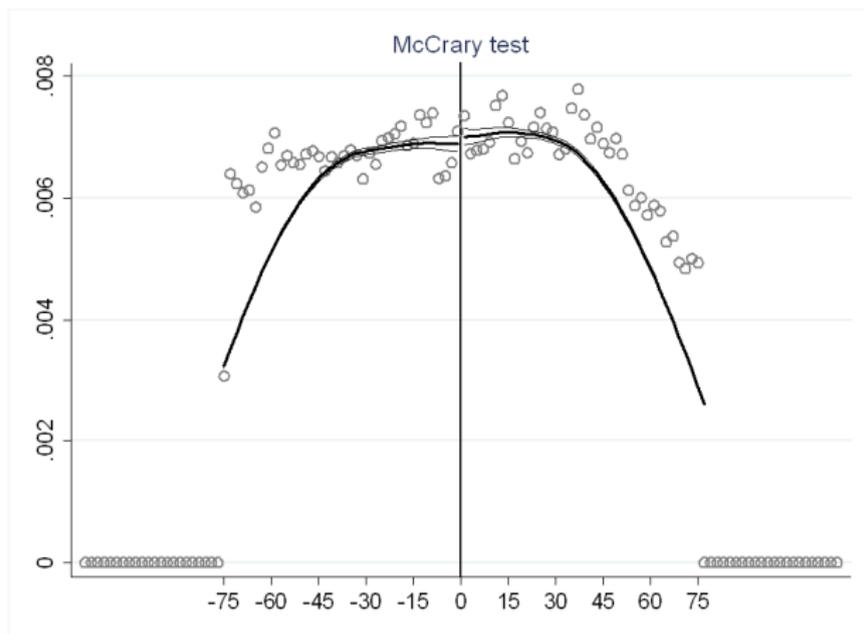
c(cutoff) specifies the RD cutoff. The default is $c(0)$.

p(pvalue) for the order of the global polynomial used to approximate the population conditional mean functions. The default is $p(4)$.

binselect(binmethod) for selecting the number of bins. E.g., **es** specifies the optimal evenly spaced method using spacings estimators.

graph_options(gphopts) graphical options

RDD validity - McCrary test



RDD validity - McCrary test

DCdensity implements standard sufficient conditions for identification in the regression discontinuity design continuity of the conditional expectation of counterfactual outcomes in the running variable.

```
DCdensity Z, breakpoint(0) generate(Xj Yj r0 fhat se_fhat) graph-  
name(DCdensity_example.eps)
```

where Z is the running variable

breakpoint for the threshold/cutoff value in the running var, which determines the two samples (e.g., control and treatment units in RD settings). The default is (0)

local linear smoother on the scatterplot (X_j, Y_j) , $r0$ for the values above and below the running var, *fhat* estimation of the density function, and *se_fhat* the standard errors of the estimation of the density function

Fuzzy Regression Discontinuity Design (RDD)

First stage

$$\text{Years of Schooling}_i = \alpha_0 + \alpha_1(\text{Treatment}_i) + \alpha_2 F(\text{Age in months}_i) + \alpha_3 X_i + \varepsilon_i \quad (1)$$

Reduced-form

$$\text{LMkt outcomes}_i = \beta_0 + \beta_1(\text{Treatment}_i) + \beta_2 F(\text{Age in months}_i) + \beta_3 X_i + \omega_i \quad (2)$$

Second stage: 2SLS

$$\text{LMkt outcomes}_i = \delta_0 + \delta_1(\widehat{\text{Years of Schooling}}_i) + \delta_2 F(\text{Age in months}_i) + \delta_3 X_i + \mu_i \quad (3)$$

X_i survey year dummies, birth states dummies, urban status, economic sector

Non-parametric analysis: rdbwselect and rdrobust

rdbwselect implements bandwidth selectors for local-polynomial RD estimators proposed in Calonico, Cattaneo, and Titiunik (2014). It also computes the bandwidth selection procedures

```
rdbwselect depvar runvar [if] [in] [,c(cutoff) p(pvalue) q(qvalue)  
rho(rhovalue) kernel(kernelfn) bwselect(bwmethod) vce(vcemethod)  
all]
```

Non-parametric analysis: rdbwselect and rdrobust

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rho(rhovalue) kernel(kernelfn) bwselect(bwmethod) vce(vcemethod)  
all]
```

rdrobust implements local-polynomial RD point estimators with robust confidence intervals proposed in Calonico, Cattaneo, and Titiunik (2014)

```
rdrobust depvar runvar [if] [in] [,c(cutoff) p(pvalue) q(qvalue)  
fuzzy(fuzzyvar) kernel(kernelfn) h(hvalue) b(bvalue) rho(rhovalue)  
bwselect(bwmethod) delta(deltavalue) vce(vcemethod) level(level)  
all]
```

Non-parametric analysis: rdbwselect and rdrobust

q (*qvalue*) for the order of the local polynomial used to construct the bias correction. The default is $q(2)$ (local quadratic regression).

ρ (*rhovalue*) sets the pilot bandwidth, b_n , equal to h_n/ρ , where h_n is computed using the method and options chosen below.

kernel (*kernelfn*) specifies the kernel function used to construct the local polynomial estimators. Options are triangular, epanechnikov, and uniform. The default is $\text{kernel}(\text{triangular})$

fuzzy(*fuzzyvar*) for the treatment status variable implementing **fuzzy RD estimation**. The default is sharp RD design. For fuzzy RD designs, bandwidths are estimated using sharp RD bandwidth selectors for the reduced-form outcome equation.

Non-parametric analysis: Results

The evidence suggests that although **the policy raises years of schooling it did not exert impacts on labour market earnings**

Estimation method Dependent variable	First-stage				Reduced-form				2SLS			
	Years of schooling				Log of hourly earnings				Log of hourly earnings			
	(a)	(b)	(c)	(d)	(a)	(b)	(c)	(d)	(a)	(b)	(c)	(d)
Treatment	0.288** (0.142)	0.277* (0.145)	0.275** (0.125)	0.236* (0.132)	0.024 (0.020)	0.024 (0.021)	0.016 (0.018)	0.015 (0.019)				
Years of schooling									0.086 (0.068)	0.085 (0.073)	0.060 (0.063)	0.062 (0.080)
Obs.	145,035	145,035	145,035	145,035	145,035	145,035	145,035	145,035	145,035	145,035	145,035	145,035
Eff. Number of obs.	37,447	35,442	47,611	39,454	37,447	35,442	47,611	39,454	37,447	35,442	47,611	39,454
Optimal bandwidth	32.13	31.25	38.64	33.90	32.13	31.25	38.64	33.90	32.13	31.25	38.64	33.90
Survey year dummies	No	Yes	Yes	Yes	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Birth region dummies	No	No	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes
Urban status	No	No	No	Yes	No	No	No	Yes	No	No	No	Yes

Notes: *p<0.1, ** p<0.05, *** p<0.01

The sample is constructed from the 2009-2017 Mexican National Occupations and Employment Survey. Following Calonico et al. (2018) and Calonico et al. (2014) for the optimal bandwidth. Robust standard errors using EHW correction as recommended by Kolesár and Rothe (2018) in parentheses.

Parametric analysis: 2SLS, reg, iveg2

Similar to a Two-Stage Least-Squares regression (2SLS)

- **First stage**

regress performs ordinary least-squares linear regression. It can also compute robust and cluster-robust standard errors.

```
regress depvar [indepvars] [if] [in] [weight] [, options]
```

where *depvar* is the dependent variable, the exogenous variable or instrument: *years of schooling*

indepvars are independent variables: the running variable, and interacted quadratic specifications for the running variable with the treatment variable on both sides of the threshold

options for the type of standard error reported. E.g., *robust*, *cluster*, etc.

- **Reduced-form**

Similar...

```
regress depvar [indepvars] [if] [in] [weight] [, options]
```

- **IV 2SLS**

ivreg2 implements a range of single-equation estimation methods for the linear regression model: ordinary least squares (OLS), instrumental variables (IV, also known as two-stage least squares, 2SLS), the generalized method of moments (GMM), etc

```
ivreg2 depvar [varlist1] (varlist2 = varlist_iv) [if] [in] [weight]  
[options]
```

Parametric analysis: 2SLS, reg, iveg2

varlist1 are the exogenous regressors or included instruments

varlist_iv are the exogenous variables excluded from the regression or excluded instruments

varlist2 the endogenous regressors that are being instrumented, the treatment group

Parametric analysis: Results

There is no empirical evidence to suggest that the policy exerts impacts on labour market earnings

Interacted quadratic specification												
Estimation method	First-stage				Reduced-form				2SLS			
	Years of schooling				Log of hourly wages				Log of hourly wages			
Dependent variable	(a)	(b)	(c)	(d)	(a)	(b)	(c)	(d)	(a)	(b)	(c)	(d)
Treatment	0.147*	0.147*	0.137*	0.116	0.016	0.016	0.015	0.012				
	(0.082)	(0.082)	(0.081)	(0.079)	(0.012)	(0.012)	(0.011)	(0.011)				
Years of schooling									0.110	0.109	0.110	0.106
									(0.075)	(0.075)	(0.080)	(0.094)
Obs.	85,890	85,890	85,890	85,890	85,890	85,890	85,890	85,890	85,890	85,890	85,890	85,890
Survey year dummies	No	Yes	Yes	Yes	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Birth region dummies	No	No	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes
Urban status	No	No	No	Yes	No	No	No	Yes	No	No	No	Yes

*p<0.1, ** p<0.05, *** p<0.01

Robust standard errors correction as recommended by Kolesár and Rothe (2018)

Conclusions

- Fuzzy RDD implemented with Stata **to analyse policy impacts**
- Different tests can be applied with Stata for **validating** the implementation of Fuzzy RDD
 - RDD plots (rdplot)
 - Mcrary test (DCdensity)
- Stata allows the **non-parametric and parametric analysis**
 - rdrobust
 - rdbwselect
 - ivreg2

Thank you!

Aydemir, A., Kirdar, M. G. (2017), "Low Wage Returns to Schooling in a Developing Country: Evidence from a Major Policy Reform in Turkey", *Oxford Bulletin of Economics and Statistics*, 79(6), 1046–1086.

Calonico, S., M. D. Cattaneo, and R. Titiunik (2014), "Robust nonparametric confidence intervals for regression-discontinuity designs", *Econometrica*.

Grenet, J. (2013), "Is Extending Compulsory Schooling Alone Enough to Raise Earnings? Evidence from French and British Compulsory Schooling Laws", *Scandinavian Journal of Economics*, 115(1), 176–210.

McCrary, J (2008), "Manipulation of the Running Variable in the Regression Discontinuity Design: A Density Test", *Journal of Econometrics*

https://eml.berkeley.edu/~jmccrary/mccrary2006_DCdensity.pdf

<https://eml.berkeley.edu/~jmccrary/DCdensity/>

National Employment Survey (ENOE) from 2009 to 2017

- Report, *inter alia*, age in months, years of schooling, earnings, etc
- Male observations aged between 24 to 40 years when surveyed
- Born between 1975 and 1987 and aged in a range of 6-18 years at the time of the reform

Example: Non-parametric Stata commands

```
foreach var of varlist lg_inc {
  2. rdbwselect `var' arecen if $sample2b, fuzzy(year_sch) kernel(tri) all
  vce(hc2) bwselect(mserd)
  3. global `var' _bw1 = e(b_mserd)
  4. global `var' _bw2 = e(h_mserd)
  5.
. forvalues z=1(1)1 {
  6. local n= `z' + 1
  7.
. rdrobust `var' arecen if $sample2b, fuzzy(year_sch) kernel(tri) all
vce(hc2) bwselect(mserd) h(${`var' _bw`n'}) b(${`var' _bw`z'}) p(2)
  8. test Conventional
  9. test Bias
  10. test Robust
  11.
  12. }
```

Example: Non-parametric Stata output

Bandwidth estimators for fuzzy RD local polynomial regression.

Cutoff $c = 0$	Left of c	Right of c	Number of obs =	148964
-----	-----	-----	Kernel =	Triangular
Number of obs	74618	74346	VCE method =	HC2
Min of arecen	-75.000	0.000		
Max of arecen	-1.000	75.000		
Order est. (p)	1	1		
Order bias (q)	2	2		

Outcome: `lg_inc`. Running variable: `arecen`. Treatment Status: `year_sch`.

Method	BW est. (h)		BW bias (b)	
	Left of c	Right of c	Left of c	Right of c
mserd	25.747	25.747	44.446	44.446
msetwo	16.950	28.188	31.721	38.319
msesum	20.930	20.930	35.719	35.719
msecomb1	20.930	20.930	35.719	35.719
msecomb2	20.930	25.747	35.719	38.319
-----	-----	-----	-----	-----
cerrd	14.193	14.193	44.446	44.446
certwo	9.344	15.539	31.721	38.319
cersum	11.538	11.538	35.719	35.719
cercomb1	11.538	11.538	35.719	35.719
cercomb2	11.538	14.193	35.719	38.319

Example: Non-parametric Stata output

Fuzzy RD estimates using local polynomial regression.

Cutoff $c = 0$	Left of c	Right of c	Number of obs =	148964
-----+-----			BW type =	Manual
Number of obs	74618	74346	Kernel =	Triangular
Eff. Number of obs	25876	27383	VCE method =	HC2
Order est. (p)	2	2		
Order bias (q)	3	3		
BW est. (h)	25.747	25.747		
BW bias (b)	44.446	44.446		
rho (h/b)	0.579	0.579		

First-stage estimates. Outcome: year_sch. Running variable: arecen.

Method	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
Conventional	.24941	.11274	2.2124	0.027	.028454 .470372
Bias-corrected	.26205	.11274	2.3245	0.020	.041094 .483012
Robust	.26205	.12038	2.1769	0.029	.02611 .497996

Treatment effect estimates. Outcome: lg_inc. Running variable: arecen. Treatment Status: year_sch.

Method	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
Conventional	.06596	.06214	1.0615	0.288	-.055834 .187763
Bias-corrected	.05903	.06214	0.9498	0.342	-.062773 .180824
Robust	.05903	.06641	0.8888	0.374	-.071138 .189189

Example: Non-parametric Stata output

Sharp RD estimates using local polynomial regression.

Cutoff $c = 0$	Left of c	Right of c		
Number of obs	74618	74346	Number of obs =	148964
Eff. Number of obs	25876	27383	BW type =	Manual
Order est. (p)	2	2	Kernel =	Triangular
Order bias (q)	3	3	VCE method =	HC2
BW est. (h)	25.747	25.747		
BW bias (b)	44.446	44.446		
rho (h/b)	0.579	0.579		

Outcome: `lg_inc`. Running variable: `arecen`.

Method	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
Conventional	.01645	.01721	0.9558	0.339	-.017284	.050188
Bias-corrected	.01556	.01721	0.9037	0.366	-.018181	.049292
Robust	.01556	.01839	0.8458	0.398	-.020492	.051603

Example: Parametric Stata commands

```
*First stage
*Spline - Quadratic specification
reg year_sch aTER arecenaTER arecen2aTER arecenaTER_UT arecen2aTER_UT,
robust

*Reduced form
*Spline - Quadratic specification
reg lg_inc aTER arecenaTER arecen2aTER arecenaTER_UT arecen2aTER_UT, robust

*Second stage
*Spline Quadratic specification
ivreg2 lg_inc (year_sch = aTER) arecenaTER arecen2aTER arecenaTER_UT
arecen2aTER_UT, robust endog (year_sch)
```

Example: Parametric Stata output

First stage

Linear regression

Number of obs = 82,125
F(5, 82119) = 37.97
Prob > F = 0.0000
R-squared = 0.0023
Root MSE = 4.0209

year_sch	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
aTER	.1658821	.0854494	1.94	0.052	-.0015982	.3333624
arecenaTER	.0033887	.0065208	0.52	0.603	-.0093921	.0161695
arecen2aTER	.0000339	.0001599	0.21	0.832	-.0002795	.0003473
arecenaTER_UT	-.0006796	.0074534	-0.09	0.927	-.0152881	.013929
arecen2aTER_UT	-.0002252	.0001806	-1.25	0.212	-.0005793	.0001288
_cons	10.3233	.0648346	159.23	0.000	10.19622	10.45037

Example: Parametric Stata output

Reduced-form

Linear regression

Number of obs = 82,125
F(5, 82119) = 9.21
Prob > F = 0.0000
R-squared = 0.0005
Root MSE = .61498

lg_inc	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
aTER	.0170504	.013021	1.31	0.190	-.0084706	.0425714
arecenaTER	-.0007443	.0009899	-0.75	0.452	-.0026846	.0011959
arecen2aTER	-.0000159	.0000244	-0.65	0.514	-.0000636	.0000318
arecenaTER_UT	-.000218	.001136	-0.19	0.848	-.0024446	.0020086
arecen2aTER_UT	8.67e-06	.0000276	0.31	0.754	-.0000455	.0000628
_cons	3.111498	.0098806	314.91	0.000	3.092132	3.130864

