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 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

Years of schooling

Men born between 1975 and 1987

Distance in months from the 12th birthday

Sample average within bin  Polynomial fit of order 2
RDD validity - Discontinuity plots

Log of hourly earnings

Men born between 1975 and 1987

Distance in months from the 12th birthday

- Sample average within bin
- Polynomial fit of order 2
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)`.
**RDD validity - Discontinuity plots**

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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)`.

`p(pvalue)` for the order of the global polynomial used to approximate the population conditional mean functions. The default is `p(4)`.
**RDD validity - Discontinuity plots**

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

\[
\text{rdplot } \text{depvar runvar [if] [in] [, } \text{c(cutoff)} \text{ p(pvalue)} \text{ binselect(binmethod)} \text{ graph_options(gphopts)}]\]

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).
- **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

McCrary test

-75 -60 -45 -30 -15 0 15 30 45 60 75
**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.

```stata
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 $(Xj, Yj)$, $r0$ 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.
Stata in applied economics: Fuzzy RDD

Fuzzy Regression Discontinuity Design (RDD)

First stage

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

Reduced-form

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

Second stage: 2SLS

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

\( X_i \) 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

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]
```

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).

`rho(rhovalue)` sets the pilot bandwidth, `b_n`, equal to `h_n/rho`, 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 `kernel(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

<table>
<thead>
<tr>
<th>Estimation method</th>
<th>Dependent variable</th>
<th>First-stage</th>
<th>Reduced-form</th>
<th>2SLS</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Years of schooling</td>
<td>Log of hourly earnings</td>
<td>Log of hourly earnings</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(a)</td>
<td>(b)</td>
<td>(c)</td>
</tr>
<tr>
<td>Treatment</td>
<td></td>
<td>0.288** 0.277* 0.275** 0.236*</td>
<td>0.024</td>
<td>0.024</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.142) (0.145) (0.125) (0.132)</td>
<td>(0.020)</td>
<td>(0.021)</td>
</tr>
</tbody>
</table>

| 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   | Yes | 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

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.
Parametric analysis: 2SLS, reg, ivreg2

- 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

\textit{varlist1} are the exogenous regressors or included instruments

\textit{varlist\_iv} are the exogenous variables excluded from the regression or excluded instruments

\textit{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.

<table>
<thead>
<tr>
<th></th>
<th>2SLS</th>
<th>(a)</th>
<th>(b)</th>
<th>(c)</th>
<th>(d)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Treatment</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.110</td>
</tr>
<tr>
<td>(0.075)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.106</td>
</tr>
<tr>
<td>Years of schooling</td>
<td>0.109</td>
<td>0.110</td>
<td>0.106</td>
<td>0.080</td>
<td>0.094</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Estimation method</th>
<th>First-stage</th>
<th>Reduced-form</th>
<th>2SLS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dependent variable</td>
<td>Year of schooling</td>
<td>Log of hourly wages</td>
<td>Log of hourly wages</td>
</tr>
<tr>
<td>Treatment</td>
<td>0.147*</td>
<td>0.016</td>
<td>0.110</td>
</tr>
<tr>
<td>(0.082)</td>
<td>0.137*</td>
<td>0.016</td>
<td>0.109</td>
</tr>
<tr>
<td>Years of schooling</td>
<td>0.116</td>
<td>0.015</td>
<td>0.110</td>
</tr>
<tr>
<td>(0.079)</td>
<td></td>
<td>0.011</td>
<td>0.080</td>
</tr>
</tbody>
</table>

- *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)
  - Mccrary test (DCdensity)

- Stata allows the non-parametric and parametric analysis
  - rdrobust
  - rdbwselect
  - ivreg2
Thank you!


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

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.

<table>
<thead>
<tr>
<th>Cutoff c = 0</th>
<th>Left of c</th>
<th>Right of c</th>
<th>Number of obs = 148964</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of obs</td>
<td>74618</td>
<td>74346</td>
<td>Kernel Triangular</td>
</tr>
<tr>
<td>Min of arecen</td>
<td>-75.000</td>
<td>0.000</td>
<td>VCE method = HC2</td>
</tr>
<tr>
<td>Max of arecen</td>
<td>-1.000</td>
<td>75.000</td>
<td></td>
</tr>
<tr>
<td>Order est. (p)</td>
<td>1</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>Order bias (q)</td>
<td>2</td>
<td>2</td>
<td></td>
</tr>
</tbody>
</table>


<table>
<thead>
<tr>
<th>Method</th>
<th>BW est. (h)</th>
<th>BW bias (b)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Left of c</td>
<td>Right of c</td>
</tr>
<tr>
<td>mserd</td>
<td>25.747</td>
<td>25.747</td>
</tr>
<tr>
<td>msetwo</td>
<td>16.950</td>
<td>28.188</td>
</tr>
<tr>
<td>msesum</td>
<td>20.930</td>
<td>20.930</td>
</tr>
<tr>
<td>msecomb1</td>
<td>20.930</td>
<td>20.930</td>
</tr>
<tr>
<td>msecomb2</td>
<td>20.930</td>
<td>25.747</td>
</tr>
<tr>
<td>cerrd</td>
<td>14.193</td>
<td>14.193</td>
</tr>
<tr>
<td>certwo</td>
<td>9.344</td>
<td>15.539</td>
</tr>
<tr>
<td>cersum</td>
<td>11.538</td>
<td>11.538</td>
</tr>
<tr>
<td>cercomb1</td>
<td>11.538</td>
<td>11.538</td>
</tr>
<tr>
<td>cercomb2</td>
<td>11.538</td>
<td>14.193</td>
</tr>
</tbody>
</table>
Example: Non-parametric Stata output

Fuzzy RD estimates using local polynomial regression.

<table>
<thead>
<tr>
<th>Cutoff c = 0</th>
<th>Left of c</th>
<th>Right of c</th>
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<tbody>
<tr>
<td>Number of obs</td>
<td>74618</td>
<td>74346</td>
<td></td>
</tr>
<tr>
<td>Eff. Number of obs</td>
<td>25876</td>
<td>27383</td>
<td></td>
</tr>
<tr>
<td>Order est. (p)</td>
<td>2</td>
<td>2</td>
<td></td>
</tr>
<tr>
<td>Order bias (q)</td>
<td>3</td>
<td>3</td>
<td></td>
</tr>
<tr>
<td>BW est. (h)</td>
<td>25.747</td>
<td>25.747</td>
<td></td>
</tr>
<tr>
<td>BW bias (b)</td>
<td>44.446</td>
<td>44.446</td>
<td></td>
</tr>
<tr>
<td>rho (h/b)</td>
<td>0.579</td>
<td>0.579</td>
<td></td>
</tr>
</tbody>
</table>


| 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 |


| 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.

<table>
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<tr>
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<td>2</td>
<td></td>
</tr>
<tr>
<td>Order bias (q)</td>
<td>3</td>
<td>3</td>
<td></td>
</tr>
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<td>25.747</td>
<td></td>
</tr>
<tr>
<td>BW bias (b)</td>
<td>44.446</td>
<td>44.446</td>
<td></td>
</tr>
<tr>
<td>rho (h/b)</td>
<td>0.579</td>
<td>0.579</td>
<td></td>
</tr>
</tbody>
</table>


| Method           | Coef.  | Std. Err. | z       | P>|z|     | [95% Conf. Interval] |
|------------------|--------|-----------|---------|---------|---------------------|
| Conventional     | 0.01645| 0.01721   | 0.9558  | 0.339   | -.017284 .050188    |
| Bias-corrected   | 0.01556| 0.01721   | 0.9037  | 0.366   | -.018181 .049292    |
| Robust           | 0.01556| 0.01839   | 0.8458  | 0.398   | -.020492 .051603    |
Example: Parametric Stata commands

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

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

*Second stage
*Spline Quadratic specification
ivreg2 lg_inc (year_sch = aTER) arecenaTER arecen2aTER arecen2aTER_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

|      | Coef.     | Robust Std. Err. | t    | P>|t|   | [95% Conf. Interval] |
|------|-----------|------------------|------|-------|---------------------|
| year_sch |           |                  |      |       |                     |
| aTER  | 0.1658821 | 0.0854494        | 1.94 | 0.052 | -0.015982 to 0.333624 |
| arecenaTER | 0.0033887 | 0.0065208        | 0.52 | 0.603 | -0.0093921 to 0.0161695 |
| arecen2aTER | 0.0000339 | 0.0001599        | 0.21 | 0.832 | -0.0002795 to 0.0003473 |
| arecenaTER_UT | -0.0006796 | 0.0074534        | -0.09 | 0.927 | -0.0152881 to 0.013929 |
| arecen2aTER_UT | -0.0002252 | 0.0001806        | -1.25 | 0.212 | -0.0005793 to 0.0001288 |
| _cons      | 10.3233   | 0.0648346        | 159.23 | 0.000 | 10.19622 to 10.45037  |
Example: Parametric Stata output

Reduced-form

Linear regression

|                     | Coef. | Std. Err. | t     | P>|t|    | [95% Conf. Interval] |
|---------------------|-------|-----------|-------|--------|-----------------------|
| lg_inc              |       |           |       |        |                       |
| aTER                | 0.0170504 | 0.013021 | 1.311 | 0.190  | -0.0084706, 0.0425714 |
| arecenaTER          | -0.0007443 | 0.0009899 | -0.752 | 0.452  | -0.0026846, 0.0011959 |
| arecen2aTER         | -0.0000159 | 0.0002444 | -0.655 | 0.514  | -0.0000636, 0.0000318 |
| arecenaTER_UT       | -0.000218  | 0.001136  | -0.192 | 0.848  | -0.0024446, 0.0020086 |
| arecen2aTER_UT      | 8.67e-06   | 0.000276  | 0.309 | 0.754  | -0.0000455, 0.0000628 |
| _cons               | 3.111498   | 0.0098806 | 314.91| 0.000  | 3.092132, 3.130864    |

Number of obs = 82,125
F(5, 82119) = 9.21
Prob > F = 0.0000
R-squared = 0.0005
Root MSE = 0.61498
Example: Parametric Stata output

IV (2SLS) estimation

Estimates efficient for homoskedasticity only
Statistics robust to heteroskedasticity

Number of obs = 82125
F( 5, 82119) = 10.35
Prob > F = 0.0000

Centered R2 = 0.1278
Uncentered R2 = 0.9672
Root MSE = 0.5745

| lg_inc   | Coef. | Std. Err. | z    | P>|z| | [95% Conf. Interval] |
|----------|-------|-----------|------|-----|----------------------|
| year_sch | 0.1027862 | 0.0731135 | 1.41 | 0.160 | -0.0408136 to 0.246086 |
| arecena2TER | -0.0010927 | 0.0010853 | -1.01 | 0.314 | -0.003198 to 0.0010845 |
| arecena2aTER | -0.0000194 | 0.0000219 | -0.89 | 0.375 | -0.0000623 to 0.0000235 |
| arecenaTER_UT | -0.0001482 | 0.0010205 | -0.15 | 0.885 | -0.0021484 to 0.001852 |
| arecena2TER_UT | 0.0000318 | 0.0000209 | 1.52 | 0.128 | -0.913e-06 to 0.0000728 |
| cons      | 2.855406  | 0.7617748  | 2.69 | 0.007 | 1.5573543 to 3.543457  |

Underidentification test (Kleibergen-Paap rk LM statistic): 3.768
Chi-sq(1) P-val = 0.0523

Weak identification test (Kleibergen-Paap rk Wald F statistic): 3.769
Stock-Yogo weak ID test critical values: 10% maximal IV size 16.38
15% maximal IV size 8.96
20% maximal IV size 6.66
25% maximal IV size 5.53

NB: Critical values are for Cragg-Donald F statistic and i.i.d. errors.

Hansen J statistic (overidentification test of all instruments): 0.000
(equation exactly identified)
-endog- option:
Endogeneity test of endogenous regressors: 0.273
Chi-sq(1) P-val = 0.6015

Regressors tested: year_sch

Instrumented: year_sch
Included instruments: arecenaTER arecena2aTER arecenaTER_UT arecena2aTER_UT
Excluded instruments: aTER