Lab8B : RDD, FE and DID

Introduction to Econometrics,Fall 2020

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Section 1

RDD in Stata

Subsection 1

Review the Theory

RDD in Stata

- Review the Theory : Summary

In a Summary

RDD in the toolkit of Causal Inference

- It is so called the **nearest** method to RCT which identify causal effect of treatment on outcome.
- RDD needs a arbitrary cut-off and agents can **imperfect** manipulate the treatment.
- Two types
  - Sharp RD
  - Fuzzy RD
- Assumption: continued at the cut-off
- Concerns:
  - Functional form
  - Bandwidth selection
  - Bin selection

Zhaopeng Qu (Nanjing University) Lecture 10: Regresssion Discontuity Design 12/10/2020 100 / 100

RDD in Stata

- Review the Theory : Main idea

Main Idea of Regression Discontinuity Design

- Regression Discontinuity Design (RDD) exploits the facts that:
  - Some rules are *arbitrary* and generate a *discontinuity* in treatment assignment.
  - The treatment assignment is determined based on whether a unit exceeds some threshold on a variable (**assignment variable**, **running variable** or **forcing variable**)
  - Assume other factors *do NOT change* abruptly at threshold.
  - Then any change in outcome of interest can be attributed to the assigned treatment.

RDD in Stata

- Review the Theory : Two types

Sharp RDD and Fuzzy RDD

- In general, depending on enforcement of treatment assignment, RDD can be categorized into two types:
  1. **Sharp RDD**: nobody below the cutoff gets the "treatment", everybody above the cutoff gets it
     - Everyone follows treatment assignment rule (all are compliers).
     - Local randomized experiment with perfect compliance around cutoff.
  2. **Fuzzy RDD**: the probability of getting the treatment jumps discontinuously at the cutoff (NOT jump from 0 to 1)
     - Not everyone follows treatment assignment rule.
     - Local randomized experiment with partial compliance around cutoff.
     - Using initial assignment as an instrument for actual treatment.

RDD in Stata

- Review the Theory ： Assumption
  - **Deterministic Assumption**

$$D_i = 1(X_i \geq c)$$

  - Treatment assignment is a deterministic function of the assignment variable X_i and the threshold c.
  - **Continuity Assumption**
    - $E[Y_{1i}|X_i]$ and $E[Y_{0i}|X_i]$ are continuous at $X_i = c$
  - Assume potential outcomes do not change at cutoff.
  - This means that except treatment assignment, all other unobserved determinants of Y_i are continuous at cutoff c.
  - This implies no other confounding factor affects outcomes at cutoff c.
  - Any observed discontinuity in the outcome can be attributed to treatment assignment.

RDD in Stata

- Review the Theory : Identification in Sharp RD

Sharp RDD specification

- A simple RD regression is

$$Y_i = \alpha + \rho D_i + \gamma(X_i - c) + u_i$$

  - Y_i is the outcome variable
  - D_I is the the treatment variable(indepent variable)
  - X_i is the running variable
  - c is the value of cut-off
  - u_i is the error term including other factors

- **Qustion**: Which parameter do we care about the most?

- Review the Theory : Identification in Sharp RD
  - More generally,we could also estimate two separate regressions for each side respectively.

$$
\begin{aligned}
Y_i^b &= \beta^b + f(X_i^b - c) + u_i^b \\
Y_i^a &= \beta^a + g(X_i^a - c) + u_i^a
\end{aligned}
$$

  - Can do all in one step; just use all the data at once and estimate:

$$Y_i = \alpha + \rho D_i + f(X_i - c) + D_i \times h(X_i - c) + u_i$$

  where D_i is a dummy variable for treated status.

RDD in Stata

- Review the Theory : Identification in Fuzzy RD
  - Encourage Variable:

$$Z_i = 1 \; if \; assign \; to \; treatment \; group$$
$$Z_i = 0 \; if \; assign \; to \; control \; group$$

  - Then the **First Stage** of FRD regression:

$$P(D_i = 1|x_i) = \alpha_1 + \phi Z_i + f(x_i - c) + Z_i \times g(x_i - c) + \eta_{1i}$$

  - The **second stage** regression is

$$Y_i = \alpha_2 + \delta \hat{D}_i + f(x_i - c) + \hat{D}_i \times g(x_i - c) + \eta_{2i}$$

  - The **reduced form** regression in FRD is

$$Y_i = \alpha_3 + \beta Z_i + f(x_i - c) + Z_i \times g(x_i - c) + \eta_{3i}$$

Subsection 2

Introduction : Package & Commands

RDD in Stata

- Introduction : Package & Commands
  - Package : [Install Link]
  - **rdrobust** package : inference and graphical procedures using local polynomial and partitioning regression methods.
    - ⋆ -*rdrobust*- : Local Polynomial Regression Discontinuity Estimation with Robust Bias-Corrected Confidence Intervals and Inference Procedures.
    - ⋆ -*rdbwselect*- : Data-driven Bandwidth Selection,
    - ⋆ -*rdplot*- : Data-Driven Regression Discontinuity Plots.
  - **rddensity** package : manipulation testing using local polynomial density methods.
  - **Others** : -*cmogram*- ; -*rd*- ; -*rdcv*- ; -*DCdensity*- ; . . .

Subsection 3

Example for Sharp RDD

RDD in Stata

- Example for Sharp RDD
  - Data : the dataset comes from a study on **party advantages** in **U.S. Senate elections** for the period 1914–2010.
  - We focus here on the RD effect of **the Democratic party winning a U.S. Senate seat** on **the vote share obtained in the following election for that same seat**.
  - The unit of observation is the **state**.
  - Main variables :
    - ★ *demmv* : ranges from -100 to 100 and records the Democratic party's margin of victory in the statewide election for a given U.S. Senate seat (the vote share of the Democratic party − the vote share of its strongest opponent).
    - ★ *demvoteshfor2* : ranges from 0 to 100 and records the Democratic vote share in the following election for the same seat.
  - To estimate the **incumbency advantage of parties** with an RD design.

RDD in Stata

- Example for Sharp RDD
  - Re-labeling the three main variables

```
. use senate, clear
. sum

    Variable |        Obs        Mean    Std. Dev.       Min        Max
-------------+---------------------------------------------------------
       state |      1,390    40.01367    21.99304          1         82
        year |      1,390     1964.63    28.05466       1914       2010
       dopen |      1,380    .2471014    .4314826          0          1
  population |      1,390     3827919     4436950      78000   3.73e+07
presdemvot~1 |      1,387    46.11975    14.31701          0   97.03408
-------------+---------------------------------------------------------
       demmv |      1,390    7.171159    34.32488       -100        100
demvoteshl~1 |      1,349    52.69048     18.2706          0        100
demvoteshl~2 |      1,308    52.86918    18.23913          0        100
demvoteshf~1 |      1,341    52.41856    18.36641          0        100
demvoteshf~2 |      1,297    52.66627    18.12219          0        100
-------------+---------------------------------------------------------
  demwinprv1 |      1,349    .5441067    .4982355          0          1
  demwinprv2 |      1,308     .543578    .4982879          0          1
    dmidterm |      1,390    .5136691     .499993          0          1
    dpresdem |      1,390    .3884892    .4875822          0          1
```

RDD in Stata

- Example for Sharp RDD
  - Re-labeling the three main variables
    - ★ Assignment variable (running variable) : X
    - ★ Outcome variable: Y
    - ★ Treatment variable : T
    - ★ Threshold (cutoff) for treatment assignment : c=0

RDD in Stata

- Example for Sharp RDD
  - Re-labeling the three main variables

```
. rename demmv X                //X--民主党获胜的差额
. rename demvoteshfor2 Y        //Y--t+2期民主党得票数

. gen T=.
. replace T=0 if X<0 & X!=.
. replace T=1 if X>=0 & X!=.
 /* the Democratic party wins the election for that seat.*/

. label var T "Democratic Win at t"
```

RDD in Stata

- Example for Sharp RDD
  - Check RD's type

```
. gen ranwin=(X>=0)

. tab ranwin T

           |  Democratic Win at t
    ranwin |         0          1 |     Total
-----------+----------------------+----------
         0 |       640          0 |       640
         1 |         0        750 |       750
-----------+----------------------+----------
     Total |       640        750 |     1,390
```

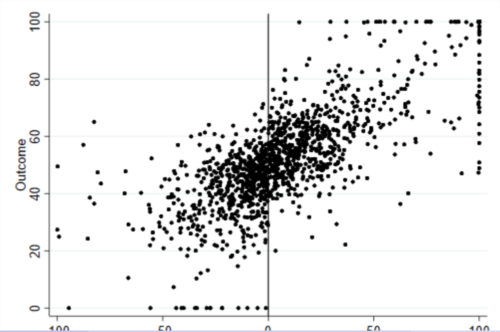
RDD in Stata

- Example for Sharp RDD
  - Show the scatter plot of the raw data (where each point is an observation).

```
. twoway (scatter Y X, msize(vsmall)                ///
      mcolor(black) xline(0, lcolor(black))),      ///
      graphregion(color(white)) ytitle(Outcome)    ///
      xtitle(Score)

. graph export fig1.png, width(500) replace
(file fig1.png written in PNG format)
```

RDD in Stata

- Example for Sharp RDD
  - Show the scatter plot of the raw data (where each point is an observation).
  - Often hard to see "jumps" or discontinuities in the outcome-score relationship by simply looking at the raw data
  - Two problems :
    - 样本太多时不够直观；
    - 实际分析时中跳跃现象可能不那么清晰。



RDD in Stata

- Example for Sharp RDD
  - Three Steps:
    1. Graph the data for visual inspection
    2. Estimate the treatment effect using regression methods
    3. Run checks on assumptions underlying research design

Subsection 4

Example for Sharp RDD : Step 1

Example for Sharp RDD

- RDD graphical analysis **:** -*rdplot*-
  - A more useful approach is to aggregate or "smooth" the data before plotting.
  - The typical RD plot presents two ingredients :
    - (i) a global polynomial fit, represented by a **solid line**, using the original **raw** data.
    - (ii) local sample means, represented by **dots**, choosing bins of the score, calculating the mean of the outcome for the observations falling within each bin, and then plotting the **average outcome in each bin** against the mid point of the bin.

Example for Sharp RDD

- RDD graphical analysis : -*rdplot*-

```
preserve
rdplot Y X, nbins(20 20) genvars support(-100 100)
gen obs = 1
collapse (mean) rdplot_mean_x rdplot_mean_y (sum) obs, by (rdplot_id)
order rdplot_id
tabstat rdplot_mean_x rdplot_mean_y obs,by(rdplot_id)
restore
```

Example for Sharp RDD

- RDD graphical analysis ： -*rdplot*-
  - Bin selection (1) ： Choosing the Location of Bins
    1. **Evenly-spaced bins** ： bins that have equal length.

```
. rdplot Y X, nbins(20 20) binselect(es)        ///
      graph_options(graphregion(color(white))   ///
      xtitle(Score) ytitle(Outcome))


RD Plot with RD plot with manually set number of bins.
         Cutoff c = 0 | Left of c  Right of c        Number of obs  =       1297
----------------------+----------------------        Kernel         =    Uniform
        Number of obs |       595         702
   Eff. Number of obs |       595         702
  Order poly. fit (p) |         4           4
     BW poly. fit (h) |   100.000     100.000
 Number of bins scale |     1.000       1.000
```

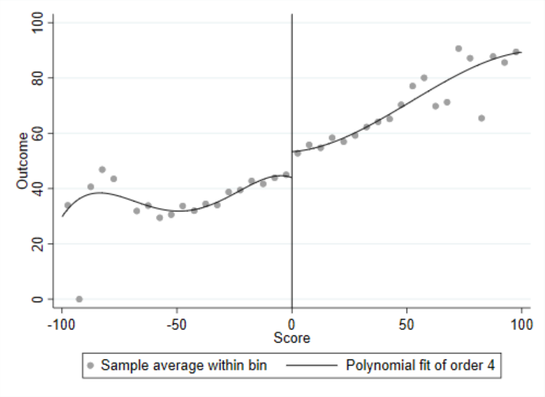
Example for Sharp RDD

- RDD graphical analysis : -*rdplot*-
  - Bin selection (1) : Choosing the Location of Bins
    1. **Evenly-spaced bins** : bins that have equal length.

```
Outcome: Y. Running variable: X.
---------------------------------------------------
                      |   Left of c   Right of c
---------------------------------------------------
         Bins selected|          20           20
    Average bin length|       5.000        5.000
     Median bin length|       5.000        5.000
---------------------------------------------------
     IMSE-optimal bins|           8            9
   Mimicking Var. bins|          15           35
---------------------------------------------------
Rel. to IMSE-optimal: |
         Implied scale|       2.500        2.222
     WIMSE var. weight|       0.060        0.084
    WIMSE bias weight|       0.940        0.916
---------------------------------------------------

. graph export fig2.png,width(500) replace
(note: file fig2.png not found)
(file fig2.png written in PNG format)
```

Example for Sharp RDD

- RDD graphical analysis : -*rdplot*-
  - Bin selection (1) : Choosing the Location of Bins
    1. **Evenly-spaced bins** : bins that have equal length.



Example for Sharp RDD

- RDD graphical analysis ： -*rdplot*-
  - Bin selection (1) ： Choosing the Location of Bins
    2. **Quantile-spaced bins** ： bins that contain (roughly) the same number of observations.

```
.   rdplot Y X, nbins(20 20) binselect(qs)        ///
      graph_options(graphregion(color(white))   ///
      xtitle(Score) ytitle(Outcome))
RD Plot with RD plot with manually set number of bins.
         Cutoff c = 0 | Left of c  Right of c        Number of obs  =       1297
----------------------+----------------------        Kernel         =    Uniform
        Number of obs |       595         702
   Eff. Number of obs |       595         702
  Order poly. fit (p) |         4           4
     BW poly. fit (h) |   100.000     100.000
 Number of bins scale |     1.000       1.000
```

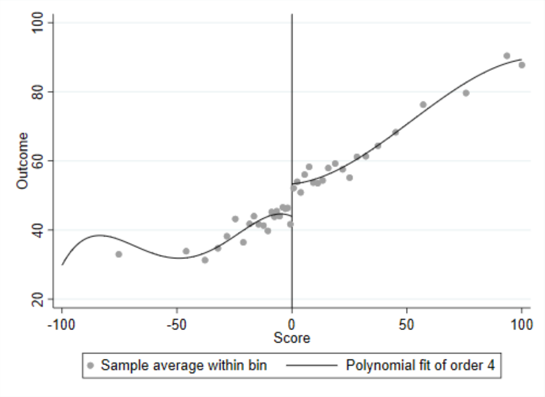
Example for Sharp RDD

- RDD graphical analysis ： -*rdplot*-
  - Bin selection (1) ： Choosing the Location of Bins
    2. **Quantile-spaced bins** ： bins that contain (roughly) the same number of observations.

```
Outcome: Y. Running variable: X.
---------------------------------------------
                      |  Left of c  Right of c
---------------------------------------------
        Bins selected |        20          20
   Average bin length |     5.000       5.000
    Median bin length |     1.912       2.771
---------------------------------------------
    IMSE-optimal bins |        21          16
  Mimicking Var. bins |        28          49
---------------------------------------------
Rel. to IMSE-optimal: |
        Implied scale |     0.952       1.250
    WIMSE var. weight |     0.537       0.339
   WIMSE bias weight  |     0.463       0.661
---------------------------------------------

. graph export fig3.png,width(500) replace
(note: file fig3.png not found)
(file fig3.png written in PNG format)
```

Example for Sharp RDD

- RDD graphical analysis : -*rdplot*-
  - Bin selection (1) : Choosing the Location of Bins
    2. **Quantile-spaced bins** : bins that contain (roughly) the same number of observations.



Example for Sharp RDD

- RDD graphical analysis : -*rdplot*-
  - Bin selection (2) : Choosing the Number of Bins
    1. Integrated Mean Squared Error (IMSE) Method
       - ★ If we choose a large number of bins (narrower) :
       - ★ **small bias** – the bins are smaller and the **local constant** fit is better.
       - ★ **less precisely** – less observations **per bin**, thus more variability within bin.
       - ★ balance squared-bias and variance so that the IMSE is (approximately) minimized.

Example for Sharp RDD

- RDD graphical analysis : -*rdplot*-
  - Bin selection (2) : Choosing the Number of Bins
    1. Integrated Mean Squared Error (IMSE) Method

```
. rdplot Y X, binselect(es)                          ///
      graph_options(graphregion(color(white))  ///
      xtitle(Score) ytitle(Outcome))

/* The IMSE criterion leads to different numbers of ES bins above and
below the cutoff.*/

RD Plot with evenly spaced number of bins using spacings estimators.
         Cutoff c = 0 | Left of c  Right of c        Number of obs  =       1297
----------------------+----------------------        Kernel         =    Uniform
        Number of obs |       595         702
   Eff. Number of obs |       595         702
  Order poly. fit (p) |         4           4
     BW poly. fit (h) |   100.000     100.000
 Number of bins scale |     1.000       1.000
```

Example for Sharp RDD

- RDD graphical analysis : -*rdplot*-
  - Bin selection (2) : Choosing the Number of Bins
    1. Integrated Mean Squared Error (IMSE) Method

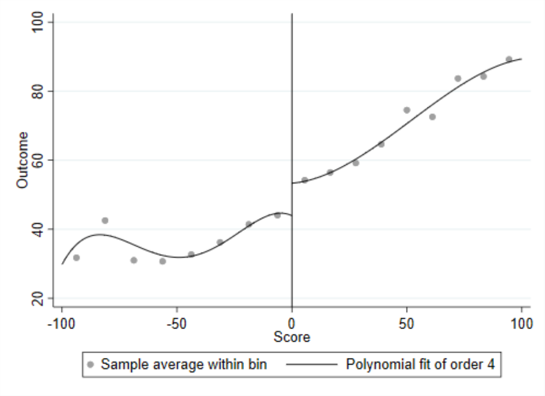
```
Outcome: Y. Running variable: X.
```

	Left of c	Right of c
Bins selected	8	9
Average bin length	12.500	11.111
Median bin length	12.500	11.111
IMSE-optimal bins	8	9
Mimicking Var. bins	15	35
Rel. to IMSE-optimal:		
Implied scale	1.000	1.000
WIMSE var. weight	0.500	0.500
WIMSE bias weight	0.500	0.500

```
. graph export fig4.png,width(500) replace
(note: file fig4.png not found)
(file fig4.png written in PNG format)
```

Example for Sharp RDD

- RDD graphical analysis： -*rdplot*-
  - Bin selection (2)： Choosing the Number of Bins
    1. Integrated Mean Squared Error (IMSE) Method



Example for Sharp RDD

- RDD graphical analysis ： -*rdplot*-
  - Bin selection (2) ： Choosing the Number of Bins

1. Integrated Mean Squared Error (IMSE) Method

```
rdplot Y X, binselect(qs)                    ///
    graph_options(graphregion(color(white))  ///
    xtitle(Score) ytitle(Outcome))
```

Example for Sharp RDD

- RDD graphical analysis : -*rdplot*-
  - Bin selection (2) : Choosing the Number of Bins
    2. Mimicking Variance (MV) Method
    - ★ "mimics" the overall variability in the raw scatter plot of the data.
    - ★ MV method leads to a larger number of bins than the IMSE method.
    - ★ More dots representing local means, thus giving a better sense of the variability of the data.

Example for Sharp RDD

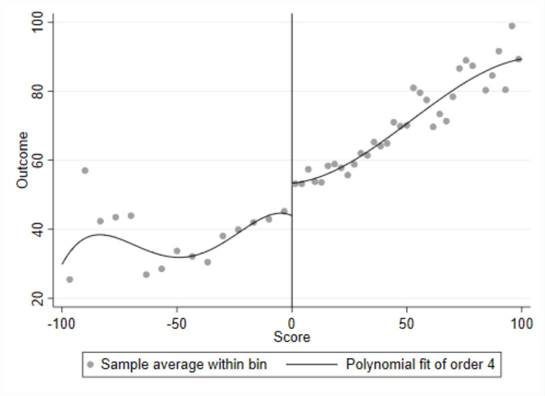
- RDD graphical analysis : -*rdplot*-
  - Bin selection (2) : Choosing the Number of Bins
    2. Mimicking Variance (MV) Method

```
.   rdplot Y X, binselect(esmv)                    ///Default
      graph_options(graphregion(color(white))  ///
      xtitle(Score) ytitle(Outcome))

RD Plot with evenly spaced mimicking variance number of bins using spacings estimato
         Cutoff c = 0 | Left of c  Right of c        Number of obs  =       1297
----------------------+----------------------        Kernel         =    Uniform
        Number of obs |       595         702
   Eff. Number of obs |       595         702
  Order poly. fit (p) |         4           4
     BW poly. fit (h) |   100.000     100.000
 Number of bins scale |     1.000       1.000
```

- RDD graphical analysis : -*rdplot*-
  - Bin selection (2) : Choosing the Number of Bins
    2. Mimicking Variance (MV) Method

```
Outcome: Y. Running variable: X.
─────────────────────────────────────────────────────────
                           │  Left of c   Right of c
─────────────────────────────────────────────────────────
            Bins selected  │         15           35
       Average bin length  │      6.667        2.857
        Median bin length  │      6.667        2.857
─────────────────────────────────────────────────────────
        IMSE-optimal bins  │          8            9
      Mimicking Var. bins  │         15           35
─────────────────────────────────────────────────────────
Rel. to IMSE-optimal:      │
            Implied scale  │      1.875        3.889
        WIMSE var. weight  │      0.132        0.017
       WIMSE bias weight   │      0.868        0.983
─────────────────────────────────────────────────────────

. graph export fig5.png,width(500) replace
(file fig5.png written in PNG format)
```

- RDD graphical analysis : -*rdplot*-
  - Bin selection (2) : Choosing the Number of Bins
    2. Mimicking Variance (MV) Method



Example for Sharp RDD

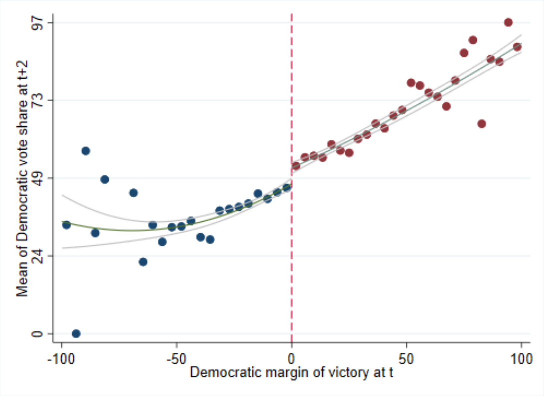
- RDD graphical analysis : -*rdplot*-
  - Bin selection (2) : Choosing the Number of Bins
    2. Mimicking Variance (MV) Method

```
rdplot Y X, binselect(qsmv)                    ///
    graph_options(graphregion(color(white))  ///
    xtitle(Score) ytitle(Outcome))
```

Example for Sharp RDD

- RDD graphical analysis : -*cmogram*-

```
. cmogram Y X, cut(0) scatter lineat(0) qfitci

. graph export fig6.png,width(500) replace
(note: file fig6.png not found)
(file fig6.png written in PNG format)
```



Subsection 5

Example for Sharp RDD : Step 2

Example for Sharp RDD

- Estimate the treatment effect using regression methods
  - There are 2 types of strategies for correctly specifying the functional form in a RDD:
    1. **Parametric**/global method: Use all available observations and Estimate treatment effects based on a specific functional form for the outcome and assignment variable relationship.
    2. **Nonparametric**/local method:Use the observations around cutoff: Compare the outcome of treated and untreated observations that lie within specific bandwidth.

Example for Sharp RDD

- Estimate the treatment effect using regression methods
  - Parametric/Global Approach (全局多项式回归)

```
sum X
local hvalueR=r(max)
local hvalueL= abs(r(min))

rdrobust Y X, h(`hvalueL' `hvalueR')      //自动选择阶数
rdrobust Y X, h(`hvalueL' `hvalueR') p(2) //二阶拟合
rdrobust Y X, h(`hvalueL' `hvalueR') p(3) //三阶拟合
```

Example for Sharp RDD

- Estimate the treatment effect using regression methods
  - Nonparametric/Local Approach：local linear regression (局部线性回归)
  - 三种方法(任选)：
    - ★ 方法一：standard least-squares estimation (OLS)
    - ★ 方法二：-rdrobust-进行的非参数估计
    - ★ 方法三：-rd-进行的非参数估计

Example for Sharp RDD

- Estimate the treatment effect using regression methods
  - Nonparametric/Local Approach : local linear regression (局部线性回归)
    - ⋆ 方法一：standard least-squares estimation (OLS)

```
. rdbwselect Y X, c(0) kernel(uni) bwselect(mserd)  //选择最优带宽h
Bandwidth estimators for sharp RD local polynomial regression.
     Cutoff c = | Left of c  Right of c            Number of obs =       1297
----------------+------------------------          Kernel        =    Uniform
                |                                  VCE method    =         NN
  Number of obs |       595         702
       Min of X |  -100.000       0.036
       Max of X |    -0.079     100.000
  Order est. (p)|         1           1
  Order bias (q)|         2           2
Outcome: Y. Running variable: X.
--------------------------------------------------------------------------------
                |        BW est. (h)           |        BW bias (b)
         Method | Left of c          Right of c | Left of c          Right of c
----------------+------------------------------+--------------------------------
          mserd |    11.597              11.597 |    22.944              22.944
--------------------------------------------------------------------------------
```

Example for Sharp RDD

- Estimate the treatment effect using regression methods
  - Nonparametric/Local Approach : local linear regression (局部线性回归)
    - ★ 方法一：standard least-squares estimation (OLS)

```
preserve
keep if X>=-11.597 & X<=11.597

local i=1
    forvalues i=2/4
    gen X`i´=X^`i´
                                            // 产生分配变量的平方、三次方、四次方

eststo x1 : qui reg Y 1.T, r
eststo x2 : qui reg Y T##c.X, r              //局部线性回归法，一阶
eststo x3 : qui reg Y T##c.(X X2), r         //局部线性回归法，选择2阶多项式
eststo x4 : qui reg Y T##c.(X X2 X3), r      //局部线性回归法，选择3阶多项式
eststo x5 : qui reg Y T##c.(X X2 X3 X4), r //局部线性回归法，选择4阶多项式

esttab x1 x2 x3 x4 x5,              ///
    star(* .1 ** .05  * .01)        ///
    nogap nonumber replace          ///
    drop(0.T*) se(%5.4f) ar2 aic(%10.4f) bic(%10.4f)
restore
```

Example for Sharp RDD

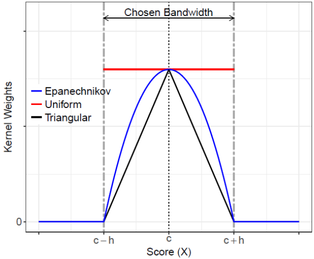
- Estimate the treatment effect using regression methods
  - Nonparametric/Local Approach : local linear regression (局部线性回归)
    - ★ 方法一：standard least-squares estimation (OLS)

	Y	Y	Y	Y	Y
1.T	9.762*	7.202*	8.832*	13.27*	16.08*
	(0.8349)	(1.6332)	(2.3939)	(3.1258)	(3.8665)
X		0.240	-1.670**	-2.793	-7.721**
		(0.2028)	(0.7598)	(1.8143)	(3.7073)
1.T#c.X		-0.0122	3.029*	0.566	6.207
		(0.2585)	(0.9956)	(2.3214)	(4.7669)
X2			-0.169**	-0.405	-2.285*
			(0.0667)	(0.3493)	(1.3548)
1.T#c.X2			0.0691	1.110**	2.708
			(0.0860)	(0.4670)	(1.7333)
X3				-0.0135	-0.265
				(0.0196)	(0.1819)
1.T#c.X3				-0.0341	0.256
				(0.0267)	(0.2288)
X4					-0.0109
					(0.0079)
1.T#c.X4					0.00921
					(0.0099)
_cons	44.28*	45.60*	41.91*	40.71*	37.51*
	(0.6010)	(1.2794)	(1.8869)	(2.5757)	(3.1696)
N	506	506	506	506	506
adj. R-sq	0.209	0.211	0.224	0.230	0.231
AIC	3709.6679	3710.3097	3704.0478	3702.2052	3703.7348
BIC	3718.1210	3727.2159	3729.4070	3736.0175	3746.0002

Standard errors in parentheses
* p<.1, ** p<.05, * p<.01

Example for Sharp RDD

- Estimate the treatment effect using regression methods
  - Nonparametric/Local Approach：local linear regression (局部线性回归)
    - ★ 方法二：-*rdrobust*-进行的非参数估计
    - ★ p：set the order of the polynomial. Default is p(1).
    - ★ kernel：set the kernel. Default is kernel(triangular).



    - ★ h：choose the bandwidth manually.
    - ★ c：sets the RD cutoff. Default is c(0).

Example for Sharp RDD

- Estimate the treatment effect using regression methods
  - Nonparametric/Local Approach : local linear regression (局部线性回归)
    - ★ 方法二：-*rdrobust*-进行的非参数估计
    - ★ bwselect() : bandwidth selection procedure to be used. Default is bwselect(mserd).
    - ★ If a smaller h :
    - ★ fewer observations—increase the variance of the estimated coefficients.
    - ★ local polynomial approximation—will reduce treatment effect biase.
    - ★ MSE : bias-variance trade-off.

Example for Sharp RDD

- Estimate the treatment effect using regression methods
  - Nonparametric/Local Approach : local linear regression (局部线性回归)
    - ★ 方法二：-*rdrobust*-进行的非参数估计

```
rdrobust Y X, kernel(uniform) p(1)
rdrobust Y X, c(0) kernel(uni) bwselect(mserd) p(2) h(11.597) all
rdrobust Y X, c(0) kernel(uni) bwselect(mserd) p(3) h(11.597) all
rdrobust Y X, c(0) kernel(uni) bwselect(mserd) p(4) h(11.597) all
```

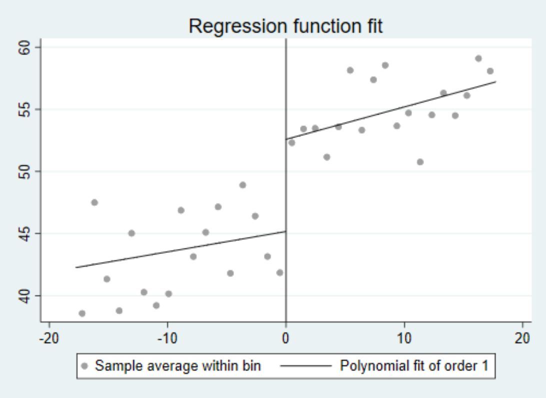
Example for Sharp RDD

- Estimate the treatment effect using regression methods
  - Nonparametric/Local Approach : local linear regression (局部线性回归)
    - ★ 方法二：-*rdrobust*-进行的非参数估计

```
* Using rdrobust and showing the associated rdplot

. rdrobust Y X, p(1) kernel(triangular) bwselect(mserd)
. eret list
. local bandwidth = e(h_l)
. rdplot Y X if abs(X) <= `bandwidth´, p(1) h(`bandwidth´) kernel(triangular)

. graph export fig7.png,width(500) replace
```

Example for Sharp RDD

- Estimate the treatment effect using regression methods
  - Nonparametric/Local Approach : local linear regression (局部线性回归)
    - 方法二：-*rdrobust*-进行的非参数估计

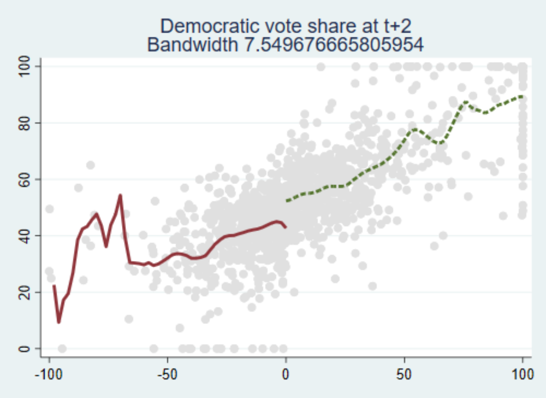


- Estimate the treatment effect using regression methods
  - Nonparametric/Local Approach：local linear regression (局部线性回归)
    - ★ 方法三：-*rd*-进行的非参数估计

```
. rd Y X, mbw(100) gr z0(0) kenel(tri)   //给出了带宽取最优带宽50%和200%的回归结果

Two variables specified; treatment is
assumed to jump from zero to one at Z=0.
 Assignment variable Z is X
 Treatment variable X_T unspecified
 Outcome variable y is Y
Command used for graph: lpoly; Kernel used: triangle (default)
Bandwidth: 7.5496767; loc Wald Estimate: 9.6449759
(93 missing values generated)
(93 missing values generated)
(93 missing values generated)
Estimating for bandwidth 7.549676665805968
------------------------------------------------------------------------------
           Y |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       lwald |   9.644976     2.1155     4.56   0.000     5.498673    13.79128
------------------------------------------------------------------------------

. graph export fig8.png,width(500) replace
(note: file fig8.png not found)
(file fig8.png written in PNG format)
```

Example for Sharp RDD

- Estimate the treatment effect using regression methods
  - Nonparametric/Local Approach : local linear regression (局部线性回归)
    - ★ 方法三：-rd-进行的非参数估计



Subsection 6

Example for Sharp RDD : Step 3

Example for Sharp RDD

- Testing the Validity of the RDD

  1. **Test involving covariates(Nonoutcome Variable)** : Test whether other covariates exhibit a jump at the discontinuity
  2. **Test sorting behavior :** Testing discontinuity in the density of assignment variable X
  3. **Falsification Tests :**
     1) Placebo Cutoffs
     2) Sensitivity to Observations near the Cutoffs
     3) Sensitivity to Bandwidth Choice

- Testing the Validity of the RDD
  1. **Test involving covariates(Nonoutcome Variable)**
     - ★ Using rdbwselect with covariates.

```
. global covariates "presdemvoteshlag1 demvoteshlag1 demvoteshlag2 demwinprv1 demwinprv2 dmidte rm dpresder
. rdrobust Y X, covs($covariates) p(1) kernel(tri) bwselect(mserd)

Covariate-adjusted sharp RD estimates using local polynomial regression.
      Cutoff c = 0 | Left of c  Right of c            Number of obs =       1213
-------------------+----------------------            BW type       =      mserd
     Number of obs |       555         658            Kernel        = Triangular
Eff. Number of obs |       326         295            VCE method    =         NN
    Order est. (p) |         1           1
    Order bias (q) |         2           2
       BW est. (h) |    17.266      17.266
       BW bias (b) |    27.178      27.178
         rho (h/b) |     0.635       0.635
Outcome: Y. Running variable: X.
--------------------------------------------------------------------------------
            Method |   Coef.    Std. Err.    z     P>|z|    [95% Conf. Interval]
-------------------+------------------------------------------------------------
      Conventional |  7.0876     1.4767   4.7995   0.000    4.19327      9.98194
            Robust |     -          -     4.0449   0.000    3.67067       10.572
--------------------------------------------------------------------------------
Covariate-adjusted estimates. Additional covariates included: 7
```

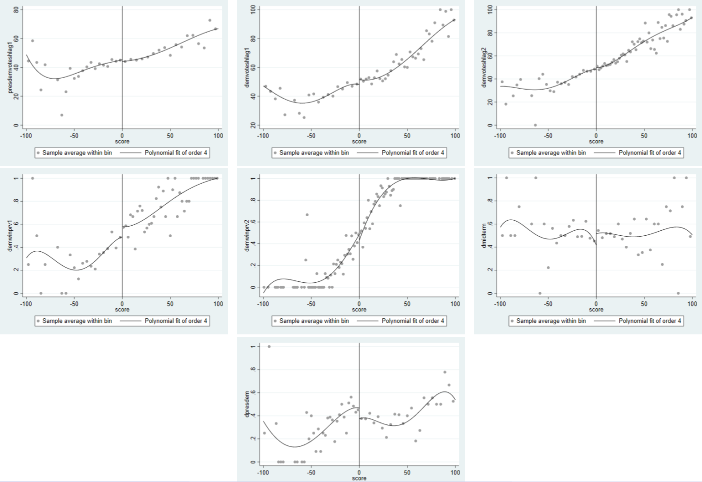
Example for Sharp RDD

- Testing the Validity of the RDD
  1. **Test involving covariates(Nonoutcome Variable)**
     - ★ Test whether other covariates exhibit a jump at the discontinuity.

```
 * There should be no jump in other covariates.
 * 从图形，似乎是存在跳跃的，但这并不严格，要看回归结果

foreach y of global covariates {
qui rdplot `y´ X, graph_options(xtitle("score")) saving(`y´)

graph export fig_`y´.png, width(500) replace
}
```

- Testing the Validity of the RDD

  1. **Test involving covariates(Nonoutcome Variable)**
     - ★ Test whether other covariates exhibit a jump at the discontinuity.



Example for Sharp RDD

- Testing the Validity of the RDD

  1. **Test involving covariates(Nonoutcome Variable)**
     - ★ Test whether other covariates exhibit a jump at the discontinuity.

```
 * 估计具体系数看是否显著

. est clear
foreach y of global covariates {
eststo : qui rdrobust `y´ X, all
}

. esttab est1 est2 est3 est4 est5 est6 est7 , ///
      se r2 mtitle star(* 0.1 ** 0.05 *** 0.01) compress
```

Example for Sharp RDD

- Testing the Validity of the RDD

1. **Test involving covariates(Nonoutcome Variable)**
   - ★ Test whether other covariates exhibit a jump at the discontinuity.

	(1) est1	(2) est2	(3) est3	(4) est4	(5) est5	(6) est6	(7) est7
Conventi~l	-1.363	2.459	1.001	0.0728	-0.0270	0.0696	-0.1000
	(1.383)	(2.052)	(1.918)	(0.0724)	(0.0712)	(0.0662)	(0.0714)
Bias-cor~d	-1.193	2.898	1.495	0.0773	-0.0386	0.0828	-0.102
	(1.383)	(2.052)	(1.918)	(0.0724)	(0.0712)	(0.0662)	(0.0714)
Robust	-1.193	2.898	1.495	0.0773	-0.0386	0.0828	-0.102
	(1.633)	(2.454)	(2.246)	(0.0866)	(0.0845)	(0.0772)	(0.0854)
N	1387	1349	1308	1349	1308	1390	1390
R-sq							

Standard errors in parentheses
* p<0.1, ** p<0.05, *** p<0.01

Example for Sharp RDD

- Testing the Validity of the RDD

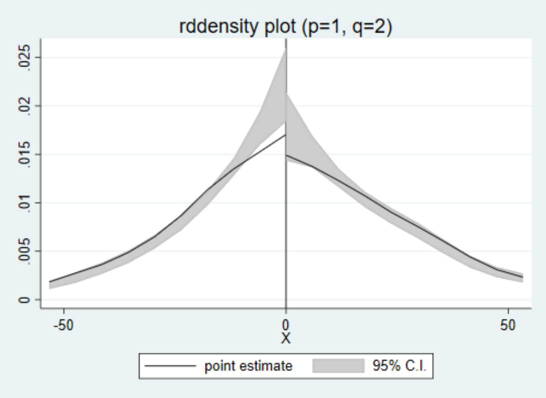
  2. **Test sorting behavior**
     - ★ Testing discontinuity in the density of assignment variable X
     - ★ -*rddensity*-

```
. rdrobust Y X
. local h = e(h_l)    //获取最优带宽
. rddensity X, p(1) h(`h´ `h´) plot

RD Manipulation Test using local polynomial density estimation.
      Cutoff c = 0 |Left of c   Right of c            Number of obs =         1390
-------------------+----------------------            Model         = unrestricted
     Number of obs |       640         750            BW method     =       manual
Eff. Number of obs |       377         346            Kernel        =   triangular
    Order est. (p) |         1           1            VCE method    =    jackknife
    Order bias (q) |         2           2
       BW est. (h) |    17.754      17.754
Running variable: X.
-----------------------------------------------
            Method |          T          P>|T|
-------------------+---------------------------
            Robust |    -1.5083         0.1315
-----------------------------------------------
```

Example for Sharp RDD

- Testing the Validity of the RDD

  2. **Test sorting behavior**
     - ★ Testing discontinuity in the density of assignment variable X
     - ★ -*rddensity*-



Example for Sharp RDD

- Testing the Validity of the RDD

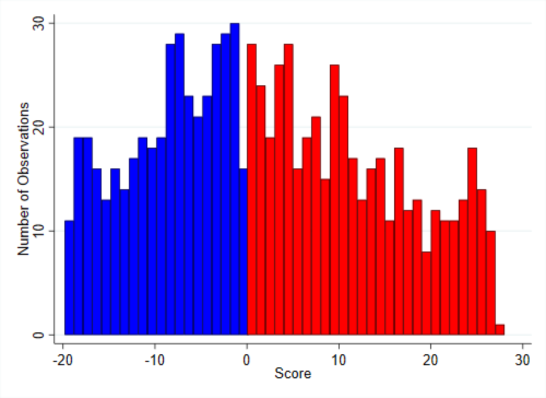
  2. **Test sorting behavior**
     - ★ Testing discontinuity in the density of assignment variable X
     - ★ Histogram(直方图)

```
. qui rddensity X
. local bandwidth_left = e(h_l)
. local bandwidth_right = e(h_r)

. twoway (histogram X if X >= -`bandwidth_left´ & X < 0, freq width(1) color(blue) lcolor(black) lwidth(vthin)) ///
     (histogram X if X >= 0 & X <= `bandwidth_right´, freq width(1) color(red) lcolor(black) lwidth(vthin)),   ///
     xlabel(-20(10)30) graphregion(color(white)) xtitle(Score) ytitle(Number of Observations) legend(off)

. graph export fig10.png, width(500) replace
(file fig10.png written in PNG format)
```

Example for Sharp RDD

- Testing the Validity of the RDD

  2. **Test sorting behavior**
     - ★ Testing discontinuity in the density of assignment variable X
     - ★ Histogram(直方图)



Example for Sharp RDD

- Testing the Validity of the RDD

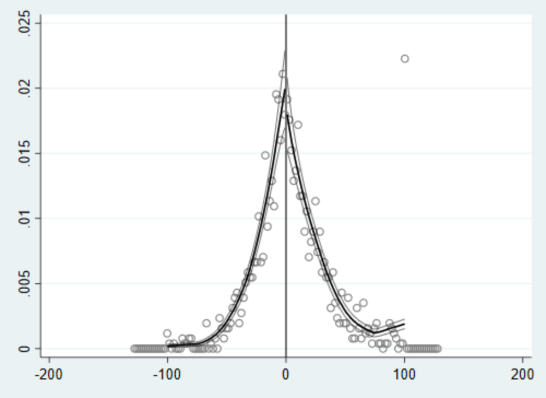
  2. **Test sorting behavior**
     - ★ Testing discontinuity in the density of assignment variable X
     - ★ a more formal test : **McCrary(2008) test** -***DCdensity***-

```
. preserve
. DCdensity X, breakpoint(0) generate(Xj Yj r0 fhat se_fhat) // McCracy test

Using default bin size calculation, bin size = 1.84133021
Using default bandwidth calculation, bandwidth = 25.8493835
Discontinuity estimate (log difference in height): -.100745626
                                                   (.117145041)
Performing LLR smoothing.
110 iterations will be performed
...........
. gen t= -.100745626/.117145041  // 产生t值，这个需要你根据系数提取出来
. display 2*ttail(50, t)          // 得到p值，50是自由度
1.6061102

. graph export fig11.png, width(500) replace
(note: file fig11.png not found)
(file fig11.png written in PNG format)
. restore
. /**可以看出在5%显著性水平下实际上Mccrary检验是通不过的，证明没有操纵**/
```

Example for Sharp RDD

- Testing the Validity of the RDD

  2. **Test sorting behavior**
     - ★ Testing discontinuity in the density of assignment variable X
     - ★ a more formal test : **McCrary(2008) test** -***DCdensity***-



- Testing the Validity of the RDD

  3. **Falsification Tests**

     - Check 1：Placebo Cutoffs
     - 选择一个不同于断点的值作为安慰剂断点 (placcebo cutoff points)，分别取真实断点两侧25%、50%、75%样本分位数处作为断点。

```
. sum X
    Variable |        Obs        Mean    Std. Dev.       Min        Max
-------------+---------------------------------------------------------
           X |      1,390    7.171159    34.32488       -100        100
. local xmax=r(max)
. local xmin=r(min)

forvalues i=1(1)3{
local jr=`xmax´/(4/(4-`i´))
local jl=`xmin´/(4/(4-`i´))
qui rdrobust Y X if X>0, c(`jr´)
est store jl`i´
qui rdrobust Y X if X<0, c(`jl´)
est store jr`i´
}

. qui rdrobust Y X ,c(0)   //加上真实断点的回归结果，作为benchmark结果
. est store jbaseline
```

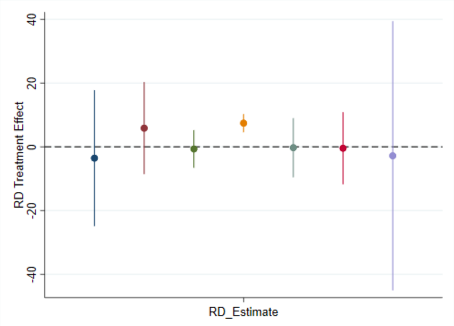
Example for Sharp RDD

- Testing the Validity of the RDD

  3. **Falsification Tests**

     - Check 1 : Placebo Cutoffs

```
. local vlist "jl1 jl2 jl3 jbaseline jr3 jr2 jr1 "
. coefplot `vlist´,  yline(0, lcolor(black) lpattern(dash)) drop(_cons) vertical ///
      graphregion(color(white)) ytitle("RD Treatment Effect") legend(off)

. graph export fig12.png, width(500) replace
(file fig12.png written in PNG format)
```



Example for Sharp RDD

- Testing the Validity of the RDD
  3. **Falsification Tests**
     - Check 2：Sensitivity to Observations near the Cutoffs
       - ★ 由于越接近断点的样本，越有动机去人为操控，删除最接近断点的样本，来观察回归是否显著（甜甜圈效应, donut hole approach）。
       - ★ 分别删除断点附近 1%，2%，3%，4% 和 5% 的样本，进行了 5 组稳健性检验。
       - ★ 图形给出了回归系数和 95% 的置信区间。

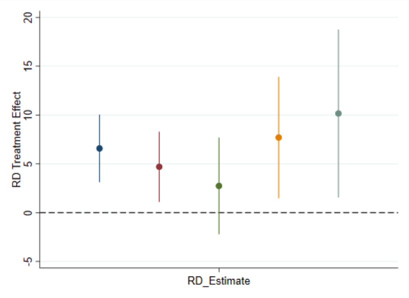
```
. sum X
. local xmax=r(max)

forvalues i=1(1)5{
local j=`xmax´*0.01*`i´
qui rdrobust Y X if abs(X)>`j´
est store obrob`i´
}
```

- Testing the Validity of the RDD

  3. **Falsification Tests**

     - Check 2 : Sensitivity to Observations near the Cutoffs

```
. local vlist "obrob1 obrob2 obrob3 obrob4 obrob5"
. coefplot `vlist´,  yline(0, lcolor(black) lpattern(dash)) drop(_cons) vertical ///
     graphregion(color(white)) legend(off)  ytitle("RD Treatment Effect")

. graph export fig13.png, width(500) replace
(note: file fig13.png not found)
(file fig13.png written in PNG format)
```



Example for Sharp RDD

- Testing the Validity of the RDD
  3. **Falsification Tests**
     - Check 3：Sensitivity to Bandwidth Choice
       - ★ 带宽长度会显著影响回归结果，一个稳健的结果要求对带宽长度不那么敏感。
       - ★ 提取最优带宽h，然后分别手动设置带宽为 h 的 25%-400% 倍，看回归结果是否仍旧显著。
       - ★ 图形给出了回归系数和95%的置信区间。

```
. qui rdrobust Y X   //自动选择最优带宽
. local h = e(h_l)   //获取最优带宽

forvalues i=1(1)8{
local hrobust=`h´*0.25*`i´
qui rdrobust Y X ,h(`hrobust´)
est store hrob`i´
}
```

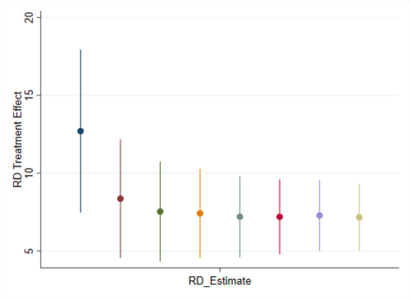
Example for Sharp RDD

- Testing the Validity of the RDD

  3. **Falsification Tests**

     - Check 3 : Sensitivity to Bandwidth Choice

```
. local vlist "hrob1 hrob2 hrob3 hrob4 hrob5 hrob6 hrob7 hrob8  "
. coefplot `vlist´,  yline(0, lcolor(black) lpattern(dash)) drop(_cons) vertical ///
      graphregion(color(white)) ytitle("RD Treatment Effect") legend(off)

. graph export fig14.png, width(500) replace
(note: file fig14.png not found)
(file fig14.png written in PNG format)
```



Subsection 7

Example for Fuzzy RDD

Example for Fuzzy RDD

- 三种方法(任选):
  - 方法一：-*rd*-
  - 方法二：-*rdrobust*-
  - 方法三：IV估计

Example for Fuzzy RDD

- 方法一：-*rd*-
  - Syntax

```
rd y d x, z0(real) strineq mbw(numlist) graph bdep oxline    ///
    kernel(rectangle) covar(varlist) x(varlist)

mbw(numlist)          //用来指定最优带宽的倍数，默认值为mbw(50 100 200)
z0(real)              //用来指定断点的位置，默认值为z0(0)，即断点为原点
*如果此处省去D，则为SRD，并根据分组变量X来计算处理变量
graph                 //根据每一带宽，画出局部线性回归图
bdep                  //根据画图来考察断点回归估计量对带宽的依赖性
oxline                //在此图的默认带宽上画出一条直线，以便识别
kernel(rectangle)     //使用均匀核（uniform），默认triangle
covar(varlist)        //用来指定加入局部线性回归的协变量
x(varlist)            //检验这些协变量在断点处是否存在跳跃（估计跳跃值
和显著性）
```

Example for Fuzzy RDD

- 方法一：-*rd*-
  - Example background
    - ★ 在美国国会,有一个民主党代表可能是被认为是对国会选区的一种treatment。
    - ★ 美国国会选区，如果有民主党众议员，对该选区的联邦政府的开支具有一定影响。
    - ★ 传统意义上，民主党会更倾向于政府，如果当选，会加大对联邦政府的开支。
    - ★ 然而直接对二者进行回归，可能会遗漏变量问题或者双向因果关系。
    - ★ 为此选择该民主党候选人的得票比例作为分组变量，Z是民主党候选人获得的选票份额。
    - ★ 以0.5为断点（在民主党与共和党的政治中，Z>=0.5，则当选，反之落选），进行RDD。

Example for Fuzzy RDD

- 方法一：-*rd*-
  - Example Data

```
. ssc inst rd, replace
. net get rd
. use votex, clear

  * lne   //选取联邦政府开支的对数
  * d     //分组变量，民主党派候选人的得票比例减去0.5，以标准化
  * win   //民主党派候选人当选
  * 另外还包括一些协变量

. desc
```

Example for Fuzzy RDD

- 方法一：-*rd*-
  - SRD

```
//OLS回归
reg lne win i votpop bla-vet
*回归结果虽然win表示当选了，会增加lne的支出，但是不显著

//选择默认的带宽以及triangle kernel进行RD
rd lne d, gr mbw(100)
*不显著，说明拥有民主党派候选人当选的选区并不能显著的增加联邦政府开支

//加入协变量进行RD，省略作图
rd lne d, mbw(100) cov(i votpop black blucllr farmer fedwrkr forborn manuf unemplyd union urban veterans)
*显示估计值虽然为正，但是依然不显著

//去掉协变量，同时估计三种带宽，并画出估计值对带宽的依赖性
rd lne d, gr bdep oxline
*改变带宽对估计值有一定的影响，但是三个估计值全部为负，且依然不显著。可以看出，各个断点回归估计量对带宽的依赖性不大。

//检验协变量在断点处是否存在跳跃
rd lne d, mbw(100) x(i votpop black  blucllr farmer fedwrkr  forborn manuf  unemplyd union urban veterans)
*farmer的P值为 0.036，其余的协变量的条件密度函数在断点处都是连续的，即只有farmer（农民占人口比例）存在跳跃。
```

Example for Fuzzy RDD

- 方法一：-*rd*-
  - FRD

```
. //生成一个新的处理变量randwin，使得randwin不完全由分组变量d决定。
. set seed 20181203
. g byte randwin=cond(uniform()<.1,1-win,win)
. tab randwin win

           |    Dem Won Race
   randwin |         0          1 |     Total
-----------+----------------------+----------
         0 |       123         14 |       137
         1 |         8        204 |       212
-----------+----------------------+----------
     Total |       131        218 |       349

 *结果显示randwin与win基本相同，但不完全相同，说明randwin不完全由分组变量d决定。
```

Example for Fuzzy RDD

- 方法一：-*rd*-
  - FRD

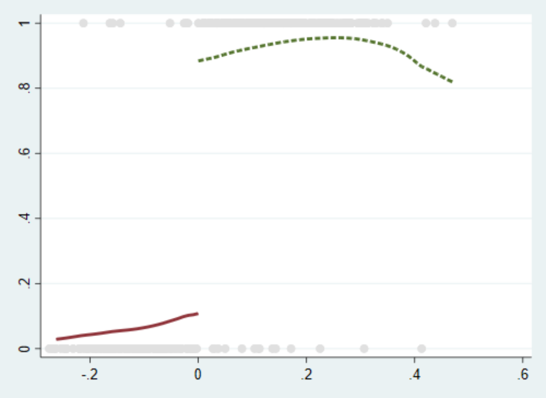
```
. //使用最优带宽与默认的triangle kernel进行FRD(含协变量)
. rd lne randwin d, gr mbw(100) cov(i votpop black blucllr farmer fedwrkr forborn manuf unemply
> d union urban veterans)

Three variables specified; jump in treatment
at Z=0 will be estimated. Local Wald Estimate
is the ratio of jump in outcome to jump in treatment.
 Assignment variable Z is d
 Treatment variable X_T is randwin
 Outcome variable y is lne
Command used for graph: lpoly; Kernel used: triangle (default)
Bandwidth: .29287776; loc Wald Estimate: -.09974965
Estimating for bandwidth .2928777592534943
A predicted value of treatment at cutoff lies outside feasible range;
switching to local mean smoothing for treatment discontinuity.
```

lne	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
numer	.0543733	.0900181	0.60	0.546	-.1220589	.2308055
denom	.8734363	.0301089	29.01	0.000	.814424	.9324487
lwald	.0622522	.1028807	0.61	0.545	-.1393903	.2638946

```
. graph export fig15.png, width(500) replace
(file fig15.png written in PNG format)
```

Example for Fuzzy RDD

- 方法一：-*rd*-
  - FRD



Example for Fuzzy RDD

- 方法二：-*rdrobust*-

```
 * options : fuzzy(fuzzyvar [sharpbw])

. rdrobust lne d, fuzzy(randwin)

Fuzzy RD estimates using local polynomial regression.
      Cutoff c = 0 | Left of c  Right of c            Number of obs =        349
-------------------+----------------------            BW type       =      mserd
     Number of obs |       131         218            Kernel        = Triangular
Eff. Number of obs |        73         105            VCE method    =         NN
    Order est. (p) |         1           1
    Order bias (q) |         2           2
       BW est. (h) |     0.142       0.142
       BW bias (b) |     0.186       0.186
         rho (h/b) |     0.762       0.762
First-stage estimates. Outcome: randwin. Running variable: d.
--------------------------------------------------------------------------------
            Method |   Coef.    Std. Err.    z     P>|z|    [95% Conf. Interval]
-------------------+------------------------------------------------------------
      Conventional |  .74178     .09171   8.0888   0.000    .562043     .921522
            Robust |     -          -     7.3050   0.000     .53871     .933789
--------------------------------------------------------------------------------
Treatment effect estimates. Outcome: lne. Running variable: d. Treatment Status: randwin.
--------------------------------------------------------------------------------
            Method |   Coef.    Std. Err.    z     P>|z|    [95% Conf. Interval]
-------------------+------------------------------------------------------------
      Conventional | -.12768     .20294  -0.6292   0.529  -.525433     .270072
            Robust |     -          -    -0.6411   0.521  -.665039       .3372
--------------------------------------------------------------------------------
```

Example for Fuzzy RDD

- 方法三：IV估计

```
. use frd.dta, clear
. sum
    Variable |        Obs        Mean    Std. Dev.       Min        Max
-------------+---------------------------------------------------------
        anno |        120    1998.667    3.831171       1993       2004
      esse_m |        120           0    6.230853        -10         10
          mc |        120    9.792913    .1016675   9.522602   9.995189
         mcn |        120    9.726134     .093931    9.46739   9.921432
          mf |        120    6.100074    .1004518   5.892969   6.368767
-------------+---------------------------------------------------------
         pen |        120    .4036111    .3359836          0   .9861111
        obsc |        120      88.175      35.007         21        184
       obscn |        120      88.175      35.007         21        184
        obsf |        120    88.11667    34.99176         21        184
        obsp |        120      88.175      35.007         21        184
-------------+---------------------------------------------------------
    anno1993 |        120   -7.45e-09    .3742406  -.1666667   .8333333
    anno1995 |        120   -7.45e-09    .3742406  -.1666667   .8333333
    anno1998 |        120   -7.45e-09    .3742406  -.1666667   .8333333
    anno2000 |        120   -7.45e-09    .3742406  -.1666667   .8333333
    anno2002 |        120   -7.45e-09    .3742406  -.1666667   .8333333
-------------+---------------------------------------------------------
    anno2004 |        120   -7.45e-09    .3742406  -.1666667   .8333333
        elig |        120          .5    .5020964          0          1
     esse_m2 |        120        38.5    32.55583          1        100
     esse_m3 |        120           0    446.6576      -1000       1000
     esse_m4 |        120      2533.3    3231.493          1      10000
-------------+---------------------------------------------------------
         sel |        120           1           0          1          1
      mc_neg |         60    9.861339    .0171739    9.83221    9.88535
      mc_pos |         60    9.724487    .0307325   9.674244   9.769611
     mcn_neg |         60    9.787027    .0135329   9.763389   9.805106
     mcn_pos |         60    9.665241    .0282369   9.618672   9.706251
-------------+---------------------------------------------------------
      mf_neg |         60    6.159085    .0148918   6.135935   6.182206
```

Example for Fuzzy RDD

- 方法三：IV估计
  - mcn, mf：非耐用品和食品支出(Y)
  - ess_m ： 已经退休的年数，负数表示还未到退休年龄
  - pen ： 退休概率，内生变量，依赖于ess_m，断点处存在不连续跳跃(X)
  - elig：退休资格虚拟变量，若ess_m>=0,elig=1,否则为0(Z)

Example for Fuzzy RDD

- 方法三：IV估计

```
. ivregress 2sls mcn (pen=elig) esse_m esse_m2 anno1995-anno2004, first robust
First-stage regressions
-----------------------

                                                Number of obs     =        120
                                                F(   8,     111)  =     177.06
                                                Prob > F          =     0.0000
                                                R-squared         =     0.9230
                                                Adj R-squared     =     0.9175
                                                Root MSE          =     0.0965
```

pen	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
esse_m	.0169943	.0031324	5.43	0.000	.0107873	.0232013
esse_m2	-.0005738	.000294	-1.95	0.054	-.0011564	8.82e-06
anno1995	.0230442	.0305492	0.75	0.452	-.0374911	.0835796
anno1998	.0508942	.0336146	1.51	0.133	-.0157153	.1175038
anno2000	.1172279	.0326428	3.59	0.000	.0525441	.1819118
anno2002	.1400281	.0327296	4.28	0.000	.0751722	.204884
anno2004	.1693907	.0333298	5.08	0.000	.1033455	.2354359
elig	.4349947	.0362406	12.00	0.000	.3631815	.5068078
_cons	.2082045	.018284	11.39	0.000	.1719736	.2444355

- 方法三：IV估计

```
Instrumental variables (2SLS) regression          Number of obs   =        120
                                                  Wald chi2(8)    =     332.96
                                                  Prob > chi2     =     0.0000
                                                  R-squared       =     0.6223
                                                  Root MSE        =     .05749

------------------------------------------------------------------------------
             |               Robust
         mcn |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         pen |  -.0983277   .0544996    -1.80   0.071    -.2051449    .0084895
      esse_m |  -.0055121   .0025899    -2.13   0.033    -.0105881    -.000436
     esse_m2 |   -.000288    .000145    -1.99   0.047    -.0005722   -3.84e-06
    anno1995 |   .0018884   .0179095     0.11   0.916    -.0332135    .0369903
    anno1998 |  -.0334648   .0181819    -1.84   0.066    -.0691007     .002171
    anno2000 |   .0121598    .019791     0.61   0.539    -.0266299    .0509495
    anno2002 |   .0210096   .0229841     0.91   0.361    -.0240384    .0660575
    anno2004 |   .0843976   .0194665     4.34   0.000     .0462439    .1225512
       _cons |    9.77691   .0244502   399.87   0.000     9.728988    9.824831
------------------------------------------------------------------------------
Instrumented:  pen
Instruments:   esse_m esse_m2 anno1995 anno1998 anno2000 anno2002 anno2004
               elig
```

- 方法三：IV估计

```
. ivregress 2sls mf (pen=elig) esse_m esse_m2 anno1995-anno2004, first robust
First-stage regressions
-----------------------

                                                Number of obs     =        120
                                                F(   8,    111)   =     177.06
                                                Prob > F          =     0.0000
                                                R-squared         =     0.9230
                                                Adj R-squared     =     0.9175
                                                Root MSE          =     0.0965

------------------------------------------------------------------------------
             |               Robust
         pen |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      esse_m |   .0169943   .0031324     5.43   0.000     .0107873    .0232013
     esse_m2 |  -.0005738    .000294    -1.95   0.054    -.0011564    8.82e-06
    anno1995 |   .0230442   .0305492     0.75   0.452    -.0374911    .0835796
    anno1998 |   .0508942   .0336146     1.51   0.133    -.0157153    .1175038
    anno2000 |   .1172279   .0326428     3.59   0.000     .0525441    .1819118
    anno2002 |   .1400281   .0327296     4.28   0.000     .0751722     .204884
    anno2004 |   .1693907   .0333298     5.08   0.000     .1033455    .2354359
        elig |   .4349947   .0362406    12.00   0.000     .3631815    .5068078
       _cons |   .2082045    .018284    11.39   0.000     .1719736    .2444355
------------------------------------------------------------------------------
```

Example for Fuzzy RDD

- 方法三：IV估计

```
Instrumental variables (2SLS) regression          Number of obs   =        120
                                                  Wald chi2(8)    =     325.13
                                                  Prob > chi2     =     0.0000
                                                  R-squared       =     0.7124
                                                  Root MSE        =     .05365

------------------------------------------------------------------------------
             |               Robust
          mf |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         pen |  -.1409689   .0523376    -2.69   0.007    -.2435487   -.0383891
      esse_m |  -.0027591   .0024779    -1.11   0.266    -.0076157    .0020975
     esse_m2 |  -.0000821   .0001355    -0.61   0.545    -.0003478    .0001835
    anno1995 |  -.0675309   .0144149    -4.68   0.000    -.0957835   -.0392782
    anno1998 |  -.1365082   .0154907    -8.81   0.000    -.1668694    -.106147
    anno2000 |    -.13855   .0177911    -7.79   0.000    -.1734199   -.1036801
    anno2002 |  -.1420846    .017727    -8.02   0.000     -.176829   -.1073403
    anno2004 |  -.1042948   .0179742    -5.80   0.000    -.1395236   -.0690661
       _cons |   6.160132   .0223924   275.10   0.000     6.116244     6.20402
------------------------------------------------------------------------------
Instrumented:  pen
Instruments:   esse_m esse_m2 anno1995 anno1998 anno2000 anno2002 anno2004
               elig
```

Section 2

FE in Stata

Subsection 1

Panel Data

Panel Data in Stata

- Panel Data
  - Panel data refers to data with observations on **multiple entities**, where each entity is observed at **two or more points in time**.
  - We focus on **balanced** and **micro** panel data.
  - **Balanced** panel: each unit of observation i is observed the same number of time periods, T.
  - **Micro** : large N, and small T, more similar to cross-section data.

Subsection 2

Review the Theory

FE in Stata

- Review the Theory
  - Fixed effects regression is a method for **controlling for omitted variables** in panel data when the omitted variables **vary across entities (states)** but do **not change over time**.
  - Specification :

$$Y_{it} = \beta_0 + \beta_1 X_{it} + \beta_2 Z_i + u_{it} \qquad (11.1)$$

- Because Z_i varies from one state to the next but is constant over time,then let $\alpha_i = \beta_0 + \beta_2 Z_i$,the Equation becomes

$$Y_{it} = \beta_1 X_{it} + \alpha_i + u_{it} \qquad (11.2)$$

- This is the **fixed effects regression model**, in which α_i are treated as *unknown intercepts* to be estimated, one for each state. The interpretation of α_i as a *state-specific intercept* in Equation (11.2).
- Arbitrarily omit the binary variable $D1_i$ for the first group. Accordingly, the fixed effects regression model in Equation (7.2) can be written equivalently as

$$Y_{it} = \beta_0 + \beta_1 X_{it} + \gamma_2 D2_i + \gamma_3 D3_i + ... + \gamma_n Dn_i + u_{it} \qquad (7.3)$$

FE in Stata

- Review the Theory
  - Estimation:
    - entity-demeaned :

$$\hat{\beta}_{demean} = \frac{\sum_{i=1}^{n} \sum_{t=1}^{T} \tilde{Y}_{it} \tilde{X}_{it}}{\sum_{i=1}^{n} \sum_{t=1}^{T} \tilde{X}_{it}^2}$$

    - first-difference estimator :

$$\hat{\beta}_{fd} = \frac{\sum_{i=1}^{n} \sum_{t=2}^{T} \Delta Y_{it} \Delta X_{it}}{\sum_{i=1}^{n} \sum_{t=2}^{T} \Delta X_{it}^2}$$

FE in Stata

- Summary
  - FE实质上就是在传统的线性回归模型中加入 N-1 个虚拟变量;
  - 使得每个截面都有自己的截距项, 截距项的不同反映了个体的某些不随时间改变的特征;
  - 我们关注的是X的系数，而非每个截面的截距项。

Subsection 3

Examples for FE

FE in Stata

- Examples for FE
  - unbalance —> balance

```
. use abond.dta, clear
. xtset id year
       panel variable:  id (unbalanced)
        time variable:  year, 1976 to 1984
                delta:  1 unit
```

- Examples for FE
  - unbalance —> balance

```
. xtdes         /*unbalanced*/
      id:  1, 2, ..., 140                                    n =        140
    year:  1976, 1977, ..., 1984                             T =          9
           Delta(year) = 1 unit
           Span(year)  = 9 periods
           (id*year uniquely identifies each observation)
Distribution of T_i:   min      5%     25%       50%       75%     95%     max
                         7       7       7         7         8       9       9
     Freq.  Percent    Cum. |  Pattern
 ---------------------------+-----------
       62     44.29   44.29 |  1111111..
       39     27.86   72.14 |  .1111111.
       19     13.57   85.71 |  .11111111
       14     10.00   95.71 |  111111111
        4      2.86   98.57 |  11111111.
        2      1.43  100.00 |  ..1111111
 ---------------------------+-----------
      140    100.00         |  XXXXXXXXX
```

FE in Stata

- Examples for FE
  - unbalance —> balance

```
. sum          /*many missing values*/
    Variable |        Obs        Mean    Std. Dev.       Min        Max
-------------+---------------------------------------------------------
          c1 |          0
         ind |      1,031    5.123181    2.678095          1          9
        year |      1,031    1979.651     2.21607       1976       1984
         emp |      1,031    7.891677    15.93492       .104    108.562
        wage |      1,031     23.9188    5.648418     8.0171    45.2318
-------------+---------------------------------------------------------
         cap |      1,031    2.507432    6.248712      .0119    47.1079
    indoutpt |      1,031    103.8012    9.938008       86.9   128.3653
           n |      1,031    1.056002    1.341506  -2.263364   4.687321
           w |      1,031    3.142988    .2630081   2.081577     3.8118
           k |      1,031   -.4415775    1.514132  -4.431217   3.852441
-------------+---------------------------------------------------------
          ys |      1,031    4.638015    .0939611   4.464758    4.85488
         rec |      1,031         516    297.7684          1       1031
      yearm1 |      1,031    1979.644    2.213454       1976       1984
          id |      1,031    73.20369    41.23333          1        140
         nL1 |        891    1.083518    1.338469  -2.095571   4.687321
-------------+---------------------------------------------------------
         nL2 |        751    1.107716    1.333478  -2.079442   4.687321
         wL1 |        891    3.132166    .2639638   2.081577     3.8118
         kL1 |        891   -.4131872    1.501461  -4.431217   3.852441
         kL2 |        751    -.392113    1.486371  -4.431217   3.852441
        ysL1 |        891    4.651039    .0923352   4.464758    4.85488
-------------+---------------------------------------------------------
```

FE in Stata

- Examples for FE
  - unbalance —> balance

```
. xtbalance, rang(1978 1982) miss(_all)    /*written by arlion*/
(331 observations deleted due to out of range)
(62 observations deleted due to missing)
(238 observations deleted due to discontinues)
. xtdes
      id:  5, 6, ..., 140                                   n =         80
    year:  1978, 1979, ..., 1982                            T =          5
           Delta(year) = 1 unit
           Span(year)  = 5 periods
           (id*year uniquely identifies each observation)
Distribution of T_i:   min      5%     25%       50%       75%     95%     max
                         5       5       5         5         5       5       5
     Freq.  Percent    Cum. |  Pattern
 ---------------------------+---------
       80    100.00  100.00 |  11111
 ---------------------------+---------
       80    100.00         |  XXXXX
```

FE in Stata

- Examples for FE
  - Data : Baum(2006)
  - 包含美国48个州1982-1988年交通死亡率相关变量:
    - fatal (交通死亡率)
    - beertax (啤酒税)
    - spircons (酒精消费量)
    - unrate (失业率)
    - perinck (人均收入,千元)
    - state (州)
    - year (年)

FE in Stata

- Examples for FE
  - Pooled OLS & Pooled OLS with Time (Wrong)

```
. use traffic, clear
. est clear
. eststo : qui reg fatal beertax
(est1 stored)
. eststo : qui reg fatal beertax i.year
(est2 stored)

. esttab, star(* .1 ** .05  * .01)     ///
      nogap nonumber replace           ///
      se(%5.4f) ar2
```

FE in Stata

- Examples for FE
  - Pooled OLS & Pooled OLS with Time (Wrong)

	fatal	fatal
beertax	0.365*	0.366*
	(0.0622)	(0.0626)
1982.year		0
		(.)
1983.year		-0.0820
		(0.1117)
1984.year		-0.0717
		(0.1117)
1985.year		-0.111
		(0.1117)
1986.year		-0.0161
		(0.1117)
1987.year		-0.0155
		(0.1117)
1988.year		-0.00103
		(0.1117)
_cons	1.853*	1.895*
	(0.0436)	(0.0857)
N	336	336
adj. R-sq	0.091	0.079

Standard errors in parentheses
* p<.1, ** p<.05, * p<.01

FE in Stata

- Examples for FE
  - Fixed effects regression

```
. xtset state year   //设定state与year为面板（个体）变量及时间变量
       panel variable:  state (strongly balanced)
        time variable:  year, 1982 to 1988
                delta:  1 unit
. xtdes
   state:  1, 4, ..., 56                                 n =          48
    year:  1982, 1983, ..., 1988                         T =           7
           Delta(year) = 1 unit
           Span(year)  = 7 periods
           (state*year uniquely identifies each observation)
Distribution of T_i:   min      5%      25%       50%       75%      95%      max
                         7       7        7         7         7        7        7
     Freq.  Percent    Cum. |  Pattern
 ---------------------------+---------
       48    100.00  100.00 |  1111111
 ---------------------------+---------
       48    100.00         |  XXXXXXX
```

FE in Stata

- Examples for FE
  - Fixed effects regression

```
. xtsum fatal beertax spircons unrate perinck state year
Variable         |      Mean   Std. Dev.       Min        Max |    Observations
-----------------+--------------------------------------------+----------------
fatal    overall |  2.040444   .5701938     .82121    4.21784 |     N =     336
         between |             .5461407   1.110077   3.653197 |     n =      48
         within  |             .1794253    1.45556   2.962664 |     T =       7
                 |                                            |
beertax  overall |   .513256   .4778442   .0433109   2.720764 |     N =     336
         between |             .4789513   .0481679   2.440507 |     n =      48
         within  |             .0552203   .1415352   .7935126 |     T =       7
                 |                                            |
spircons overall |   1.75369   .6835745        .79        4.9 |     N =     336
         between |             .6734649   .8614286   4.388572 |     n =      48
         within  |              .147792   1.255119   2.265119 |     T =       7
                 |                                            |
unrate   overall |  7.346726   2.533405        2.4         18 |     N =     336
         between |             1.953377        4.1       13.2 |     n =      48
         within  |             1.634257   4.046726   12.14673 |     T =       7
                 |                                            |
perinck  overall |  13.88018   2.253046   9.513762   22.19345 |     N =     336
         between |             2.122712    9.95087   19.51582 |     n =      48
         within  |             .8068546   11.43261   16.55782 |     T =       7
                 |                                            |
state    overall |   30.1875   15.30985          1         56 |     N =     336
         between |             15.44883          1         56 |     n =      48
         within  |                    0    30.1875    30.1875 |     T =       7
```

FE in Stata

- Examples for FE
  - Fixed effects regression

```
. xtline fatal if year==1982
. graph export fefig1.png,width(500) replace
(file fefig1.png written in PNG format)
```

FE in Stata

- Examples for FE
  - Fixed effects regression

```
. xtreg fatal beertax spircons unrate perinck, fe
Fixed-effects (within) regression               Number of obs     =        336
Group variable: state                           Number of groups  =         48
R-sq:                                           Obs per group:
     within  = 0.3526                                         min =          7
     between = 0.1146                                         avg =        7.0
     overall = 0.0863                                         max =          7
                                                F(4,284)          =      38.68
corr(u_i, Xb)  = -0.8804                        Prob > F          =     0.0000
------------------------------------------------------------------------------
       fatal |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     beertax |  -.4840728   .1625106    -2.98   0.003    -.8039508   -.1641948
    spircons |   .8169652   .0792118    10.31   0.000     .6610484    .9728819
      unrate |  -.0290499   .0090274    -3.22   0.001    -.0468191   -.0112808
     perinck |   .1047103   .0205986     5.08   0.000      .064165    .1452555
       _cons |   -.383783   .4201781    -0.91   0.362    -1.210841    .4432754
-------------+----------------------------------------------------------------
     sigma_u |  1.1181913
     sigma_e |  .15678965
         rho |  .98071823   (fraction of variance due to u_i)
------------------------------------------------------------------------------
F test that all u_i=0: F(47, 284) = 59.77                    Prob > F = 0.0000
. est store FE
```

FE in Stata

- Examples for FE
  - Fixed effects regression
  - clustered standard errors

```
. xtreg fatal beertax spircons unrate perinck, fe vce(cluster state)
Fixed-effects (within) regression               Number of obs     =        336
Group variable: state                           Number of groups  =         48
R-sq:                                           Obs per group:
     within  = 0.3526                                         min =          7
     between = 0.1146                                         avg =        7.0
     overall = 0.0863                                         max =          7
                                                F(4,47)           =      21.27
corr(u_i, Xb)  = -0.8804                        Prob > F          =     0.0000
                               (Std. Err. adjusted for 48 clusters in state)
------------------------------------------------------------------------------
             |               Robust
       fatal |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     beertax |  -.4840728   .2218754    -2.18   0.034    -.9304285    -.037717
    spircons |   .8169652   .1272627     6.42   0.000     .5609456    1.072985
      unrate |  -.0290499   .0094581    -3.07   0.004    -.0480772   -.0100227
     perinck |   .1047103   .0341455     3.07   0.004     .0360184    .1734022
       _cons |   -.383783   .7091738    -0.54   0.591    -1.810457    1.042891
-------------+----------------------------------------------------------------
     sigma_u |  1.1181913
     sigma_e |  .15678965
         rho |  .98071823   (fraction of variance due to u_i)
------------------------------------------------------------------------------
. est store FE_cse
```

FE in Stata

- Examples for FE
  - Fixed effects regression
  - Both Entity and Time Fixed Effects

```
. xtreg fatal beertax spircons unrate perinck i.year, fe vce(cluster state)
Fixed-effects (within) regression               Number of obs     =        336
Group variable: state                           Number of groups  =         48
R-sq:                                           Obs per group:
     within  = 0.4528                                         min =          7
     between = 0.1090                                         avg =        7.0
     overall = 0.0770                                         max =          7
                                                F(10,47)          =      14.13
corr(u_i, Xb)  = -0.8728                        Prob > F          =     0.0000
                               (Std. Err. adjusted for 48 clusters in state)
------------------------------------------------------------------------------
             |               Robust
       fatal |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     beertax |  -.4347195   .2442775    -1.78   0.082    -.9261425    .0567036
    spircons |    .805857   .1161087     6.94   0.000     .5722764    1.039438
      unrate |  -.0549084    .011763    -4.67   0.000    -.0785725   -.0312443
     perinck |   .0882636   .0322971     2.73   0.009     .0232901     .153237
             |
        year |
        1983 |  -.0533713   .0312438    -1.71   0.094    -.1162256    .0094831
        1984 |  -.1649828   .0439375    -3.75   0.000    -.2533737    -.076592
        1985 |  -.1997376   .0496167    -4.03   0.000    -.2995535   -.0999218
        1986 |  -.0508034   .0661756    -0.77   0.447    -.1839315    .0823248
        1987 |  -.1000728   .0756768    -1.32   0.192    -.2523149    .0521693
```

FE in Stata

- Examples for FE
  - Fixed effects regression

```
. esttab FE FE_cse FE_TW, star(* .1 ** .05  * .01)        ///
>      nogap nonumber replace se(%5.4f) ar2 drop(1982.year)
------------------------------------------------------------
                    fatal            fatal            fatal
------------------------------------------------------------
beertax            -0.484*         -0.484**          -0.435*
                 (0.1625)         (0.2219)         (0.2443)
spircons            0.817*           0.817*           0.806*
                 (0.0792)         (0.1273)         (0.1161)
unrate            -0.0290*         -0.0290*         -0.0549*
                 (0.0090)         (0.0095)         (0.0118)
perinck             0.105*           0.105*          0.0883*
                 (0.0206)         (0.0341)         (0.0323)
1983.year                                           -0.0534*
                                                   (0.0312)
1984.year                                           -0.165*
                                                   (0.0439)
1985.year                                           -0.200*
                                                   (0.0496)
1986.year                                           -0.0508
                                                   (0.0662)
1987.year                                            -0.100
                                                   (0.0757)
1988.year                                            -0.134
                                                   (0.0864)
_cons              -0.384           -0.384            0.129
                 (0.4202)         (0.7092)         (0.6238)
------------------------------------------------------------
N                     336              336              336
adj. R-sq           0.236            0.345            0.436
------------------------------------------------------------
Standard errors in parentheses
* p<.1, ** p<.05, * p<.01
```

Section 3

DID in Stata

Subsection 1

Review the Theory

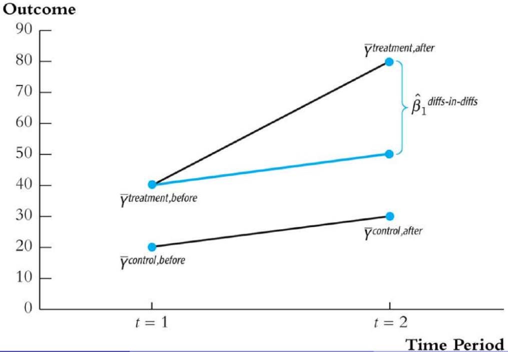
DID in Stata

- Review the Theory

DID estimator

- The DID estimator is

$$\hat{\beta}_{DID} = (\bar{Y}_{treat,post} - \bar{Y}_{treat,pre}) - (\bar{Y}_{control,post} - \bar{Y}_{control,pre})$$



DID in Stata

- Review the Theory

Regression DD - Card and Krueger

- A 2×2 matrix table

		treat or control	
		NJ=0(control)	NJ=1(treat)
pre or post	d=0(pre)	α	$\alpha+\gamma$
	d=1(post)	$\alpha+\lambda$	$\alpha+\gamma+\lambda+\delta$

- Then DID estimator

$$
\begin{aligned}
\hat{\beta}_{DID} = & (\bar{Y}_{treat,post} - \bar{Y}_{treat,pre}) - \\
& (\bar{Y}_{control,post} - \bar{Y}_{control,pre}) \\
& = (NJ_{post} - NJ_{pre}) - (PA_{post} - PA_{pre}) \\
& = [(\alpha+\gamma+\lambda+\delta) - (\alpha+\gamma)] - [(\alpha+\lambda) - \alpha] \\
& = \delta
\end{aligned}
$$

- Review the Theory
  - Specification :

$$Y_{ist} = \alpha + \beta D_{st} + \gamma Treat_s + \delta Post_t + \Gamma X'_{ist} + u_{ist}$$

    - Where D_{st} means $(Treat \times Post)_{st}$
  - Using Fixed Effect Models further to transform into

$$Y_{ist} = \beta D_{st} + \alpha_s + \delta_t + \Gamma X'_{ist} + u_{ist}$$

    - α_s is a set of groups fixed effects, which captures $Treat_s$.
    - δ_t is a set of time fixed effects, which captures $Post_t$.

Subsection 2

Examples for DID

DID in Stata

- Examples for DID
  - Data：
    - ★ 历史上A、B、C、D、E、F、G这7个地区非常相似
    - ★ 然而1994年后E、F和G三个地区（treatment group）颁布了一项政策
    - ★ 其余4个地区（control group）没有。

```
. use did, clear
```

DID in Stata

- Examples for DID

```
. * 假设政策执行时间为1994年，设置虚拟变量
. gen time = (year>=1994) & !missing(year)

. * 假设政策执行地为大于4的地方，设置虚拟变量
. gen treated = (country>4) & !missing(country)

. * 构建DID估计量，即时间和空间的交互项
. gen did = time*treated
```

- Examples for DID

```
. * DID <方法一>
. * 显然在10%水平上，政策实施有显著的负效应
. reg y did time treated, r
Linear regression                               Number of obs     =         70
                                                F(3, 66)          =       2.17
                                                Prob > F          =     0.0998
                                                R-squared         =     0.0827
                                                Root MSE          =     3.0e+09

------------------------------------------------------------------------------
             |               Robust
           y |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         did |  -2.52e+09   1.45e+09    -1.73   0.088    -5.42e+09    3.81e+08
        time |   2.29e+09   9.00e+08     2.54   0.013     4.92e+08    4.09e+09
     treated |   1.78e+09   1.05e+09     1.70   0.094    -3.11e+08    3.86e+09
       _cons |   3.58e+08   7.61e+08     0.47   0.640    -1.16e+09    1.88e+09
------------------------------------------------------------------------------

. * DID <方法二>
. qui reg y time##treated, r
```

DID in Stata

- Examples for DID

```
. * DID <方法三>
. * 与前两种方法结果一样

. *ssc install diff
. diff y, t(treated) p(time)
DIFFERENCE-IN-DIFFERENCES ESTIMATION RESULTS
Number of observations in the DIFF-IN-DIFF: 70
            Before         After
   Control: 16             24          40
   Treated: 12             18          30
            28             42
--------------------------------------------------------
 Outcome var.    | y         | S. Err. |    |t|    |  P>|t|
-----------------+-----------+---------+----------+---------
Before           |           |         |          |
   Control       |  3.6e+08  |         |          |
   Treated       |  2.1e+09  |         |          |
   Diff (T-C)    |  1.8e+09  | 1.1e+09 | 1.58     | 0.120
After            |           |         |          |
   Control       |  2.6e+09  |         |          |
   Treated       |  1.9e+09  |         |          |
   Diff (T-C)    | -7.4e+08  | 9.2e+08 | 0.81     | 0.422
                 |           |         |          |
Diff-in-Diff     | -2.5e+09  | 1.5e+09 | 1.73     | 0.088*
--------------------------------------------------------
R-square:    0.08
* Means and Standard Errors are estimated by linear regression
**Inference: *** p<0.01; ** p<0.05; * p<0.1
```

- Examples for DID
  - Test Paralled Trend
    - ★ 只有当地区在政策前足够相似才能够保证DID提取的是政策的因果效应；
    - ★ 因此，需要知道两组地区在政策前有多大差异；
    - ★ 生成年份虚拟变量×实验组虚拟变量的交互项，捕捉两组地区在每一年份的差异；
    - ★ 如果两组地区的确有Paralled Trend，那么预期在1994年前的那些交互项的回归结果将不显著，而1994年后的将显著。

DID in Stata

- Examples for DID
  - Test Paralled Trend

```
. *生成年份虚拟变量与实验组虚拟变量的交互项(此处选在政策前后各3年)
. gen Dyear = year-1994
. gen Before3 = (Dyear==-3 & treated==1)
. gen Before2 = (Dyear==-2 & treated==1)
. gen Before1 = (Dyear==-1 & treated==1)
. gen Current = (Dyear==0 & treated==1)
. gen After1 = (Dyear==1 & treated==1)
. gen After2 = (Dyear==2 & treated==1)
. gen After3 = (Dyear==3 & treated==1)
```

- Examples for DID
  - Test Paralled Trend

```
. * 将以上交互项作为解释变量进行回归
. * 可以看出Before3 Before2 Before1 的系数均不显著，After1的系数负向显著

. xtreg y time treated Before3 Before2 Before1 Current After1 After2 After3 i.year,
note: treated omitted because of collinearity
note: 1999.year omitted because of collinearity
Fixed-effects (within) regression               Number of obs     =         70
Group variable: country                         Number of groups  =          7
R-sq:                                           Obs per group:
     within  = 0.3885                                         min =         10
     between = 0.0116                                         avg =       10.0
     overall = 0.3040                                         max =         10
                                                F(16,47)          =       1.87
corr(u_i, Xb)  = -0.0654                        Prob > F          =     0.0497
------------------------------------------------------------------------------
           y |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        time |   1.62e+09   1.40e+09     1.16   0.250    -1.18e+09    4.43e+09
     treated |          0  (omitted)
     Before3 |   5.26e+08   2.30e+09     0.23   0.820    -4.10e+09    5.16e+09
     Before2 |   1.94e+09   2.30e+09     0.84   0.404    -2.69e+09    6.57e+09
     Before1 |  -4.53e+08   2.30e+09    -0.20   0.845    -5.08e+09    4.18e+09
     Current |  -8.06e+08   2.30e+09    -0.35   0.728    -5.44e+09    3.82e+09
      After1 |  -7.15e+09   2.30e+09    -3.10   0.003    -1.18e+10   -2.52e+09
      After2 |  -9.04e+08   2.30e+09    -0.39   0.696    -5.54e+09    3.73e+09
      After3 |   3.21e+08   2.30e+09     0.14   0.890    -4.31e+09    4.95e+09
```

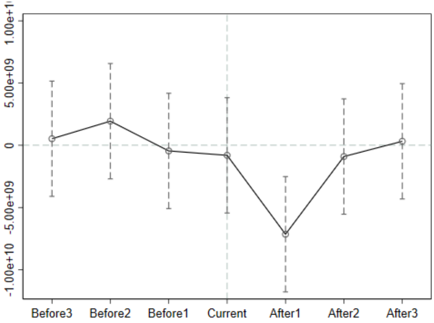
DID in Stata

- Examples for DID
  - Test Paralled Trend
  - -coefplot-图示

```
. * keep() : 保留关键变量
. * vertical : 转置
. * recast(connect) : 系数连线, 观察动态效果:
. * yline(0) : 增加直线y=0

. coefplot reg, keep(Before3 Before2 Before1 Current After1 After2 After3)   ///
      vertical recast(connect) scheme(s1mono) msymbol(circle_hollow)         ///
      yline(0, lwidth(vthin) lpattern(dash) lcolor(teal))                    ///
      xline(4, lwidth(vthin) lpattern(dash) lcolor(teal))                    ///
      ciopts(lpattern(dash) recast(rcap) msize(medium))

. graph export did.png,width(500) replace
(note: file did.png not found)
(file did.png written in PNG format)
```

DID in Stata

- Examples for DID
  - Test Paralled Trend
  - -*coefplot*-图示
    - ★ 发现系数在政策前在0附近波动，而政策后一年系数显著为负，但很快又回到0附近；
    - ★ 说明treatment group和control group可以进行比较，而政策效果可能出现在颁布后一年，随后又很快消失。



DID in Stata

Happy Christmas and New Year! & Get Good Marks in the Final Exam!