Regression Discontinuity Designs

with applications to close electoral races and public policy to increase female labor force participation

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Outline

Introduction

Setting – Estimation of treatment effects in a non-experimental setting where treatment D is determined by whether an observed "forcing" variable S exceeds a known threshold $\overline{s}$

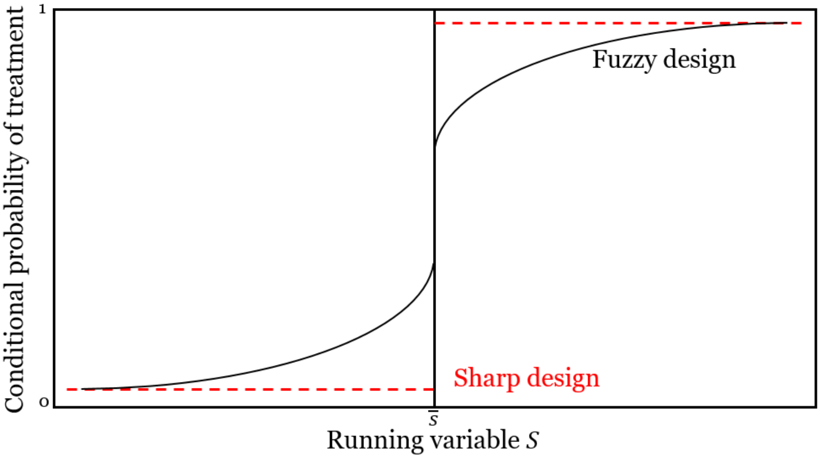
Two RD designs

1. **Sharp** – units are ranked according to S and treatment status deterministically follows from the rule $D = 1(S \geqslant \overline{s})$

2. **Fuzzy** – units are ranked according to S and assigned to the intervention according to the rule $Z = 1(S \geqslant \overline{s})$ but because of non-compliance $D \neq Z$

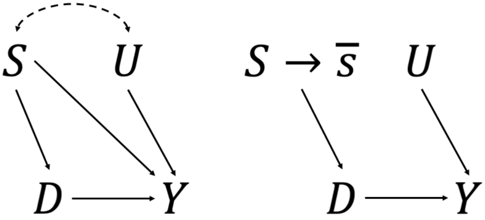
We are going to focus on sharp designs

Figure: Sharp vs. Fuzzy designs



Identification

Intuition



(A) Data generating graph (B) Limiting graph

Panel (A)

- S assigns units to treatment D
- S may independently affect Y and may be related to variables U
- S is an observable confounder

Panel (B)

- As $S \to \bar{s}$ we eliminate direct relationship between S and Y

Identification

Potential outcomes

Let Y_1 and Y_0 be the potential outcomes when $D = 1$ and $D = 0$, respectively.

The observed outcome is $Y = (1 - D)Y_0 + DY_1$.

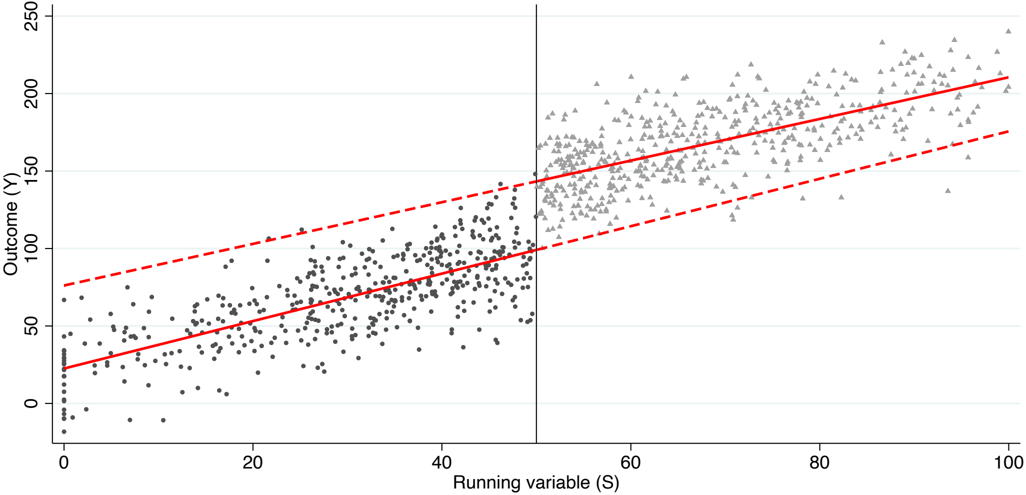
We can identify the LATE τ^{RDD} at the cut-off $S = \overline{s}$, by taking the limit of the conditional expectation of Y, i.e.

$$\tau^{RDD} = Y^+ - Y^- = \lim_{\Delta \to 0} [E(Y|S > \overline{s} + \Delta) - E(Y|S < \overline{s} - \Delta)]$$

Key identifying assumption: Continuity

Potential outcomes are continuous at $S = \overline{s}$

Continuity of potential outcomes



Estimation

Can proceed in two ways

1. **Parametrically**

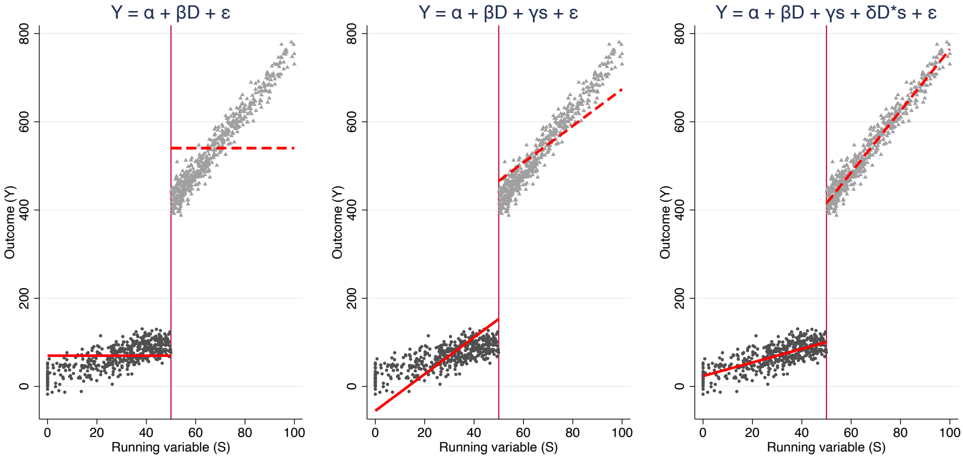
$$Y_i = \alpha + \beta D_i + \gamma s_i + \delta D_i s_i + \varepsilon_i$$

   where $\beta = \tau^{RDD}$ and $s_i = S_i - \overline{s}$

2. **Non-parametrically** – Local linear kernel regression
   Weighted regression restricted to a window (hence “local") – τ^{RDD} equals in this case the difference in intercepts of two local linear estimators, fitted on both sides of the threshold

RDD in practice

Slopes of regression lines



RDD in practice

1. **Choice of the bandwidth**

   Estimates should be robust to different bandwidths around the threshold
   Optimal bandwidth $\rightarrow$ Calonico, Cattaneo, Titiunik (2014) [in Stata `rdrobust`]

2. **Choice of the polynomial order of the regression function** [parametric]

   If the relationship between the outcome and the forcing variable is non-linear, can fit a polynomial regression model

$$
\begin{aligned}
Y_i = \alpha + \beta D_i + \gamma_1 s_i + \gamma_2 s_i^2 + \cdots + \gamma_p s_i^p \\
+ D_i(\delta_1 s_i + \delta_2 s_i^2 + \ldots \delta_p s_i^p) + \varepsilon_i
\end{aligned}
$$

   Caveat: higher-order polynomials can lead to overfitting and bias (Gelman and Imbens, 2019)

Validity tests

1. **Discontinuity in treatment at threshold**
   Any discontinuity in the relationship between outcome and treatment has to be fully attributable to treatment itself
   → Check baseline covariates do not change discontinuously at threshold

2. **No discontinuities away from the threshold**
   The only/most important discontinuity for Y should be at the threshold
   → Discontinuities at other parts of the distribution should be suspicious

3. **No jump in density of the forcing variable at the threshold**
   A jump in the density of S at the threshold is evidence of sorting/manipulation (or selective attrition)
   → Inspect the density of the forcing variable [in Stata: `histogram`, `DCdensity`, `rddensity`]

Applications

The **close-election design** has become quite popular within RDD

Exploits a feature of electoral systems wherein winners in political races are declared when a candidate gets the minimum needed share of votes.

As very close races represent exogenous assignments of a party's victory, we can use these close elections to identify the causal effect of the winner on a variety of outcomes.

The "at the margins of a close race" is crucial:

- it is at the margins of a close race that the distribution of voter preferences is the same
- if voter preferences are the same, but policies diverge at the cutoff, then **politicians** and **not voters** are driving policy making.

The exogenous shock comes from the discontinuity in the running variable – the **Margin of Victory**:

- classic example: at a vote share of just above 0.5, the Democratic candidate wins (Lee and Lemieux, 2010)
- our focus: mixed gender races – at a positive *relative* vote share the female candidate wins

$\rightarrow$ around that cutoff, random chance determined the win—hence the random assignment of D

Application # 1 – Gagliarducci and Paserman (2012)

Research questions

- Analyze probability of early termination in municipalities headed by female mayors
- Investigate moderating effect of gender composition of the municipal council

Data

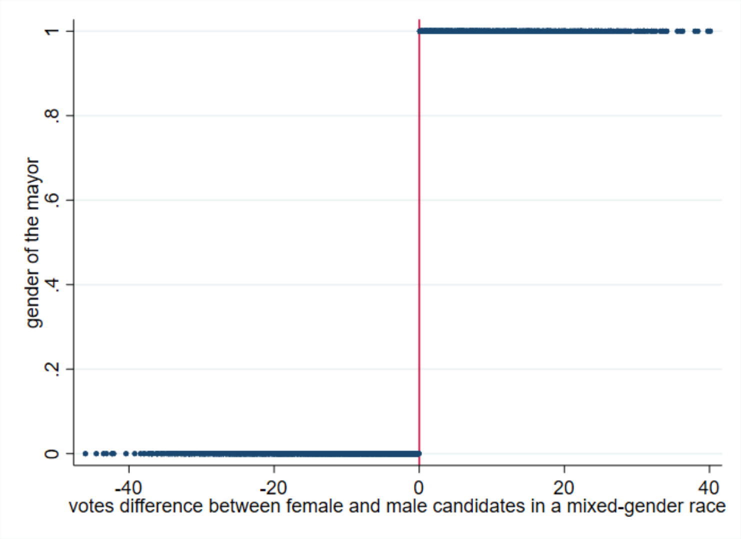
- Data on elections and mayors of Italian municipalities over the period 1993-2003

Application # 1 – Gagliarducci and Paserman (2012)

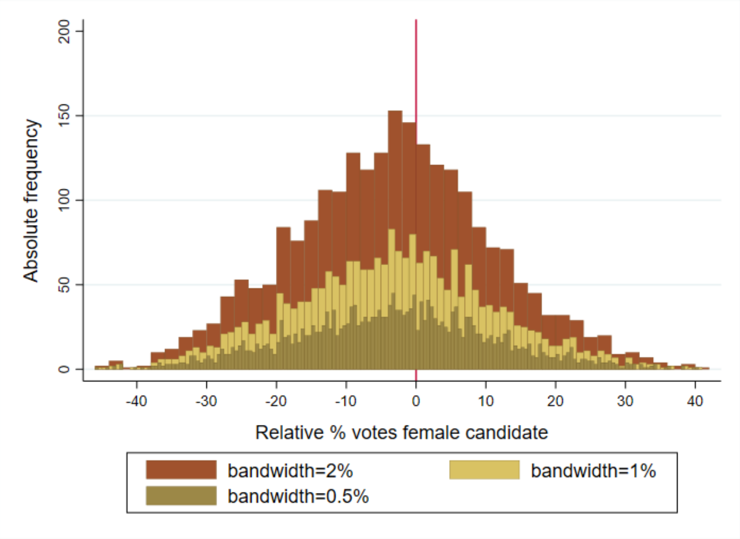
Empirical strategy

- Exploit close electoral races in a RDD set-up, focusing on mixed gender elections, i.e. those in which a male and female candidate compete (or where the two most voted candidates are a man and a woman)
- Running variable: Margin of victory of female candidates in municipal elections
- Identifying assumption: in close races win of a candidate over another is random [e.g., weather conditions on election day]

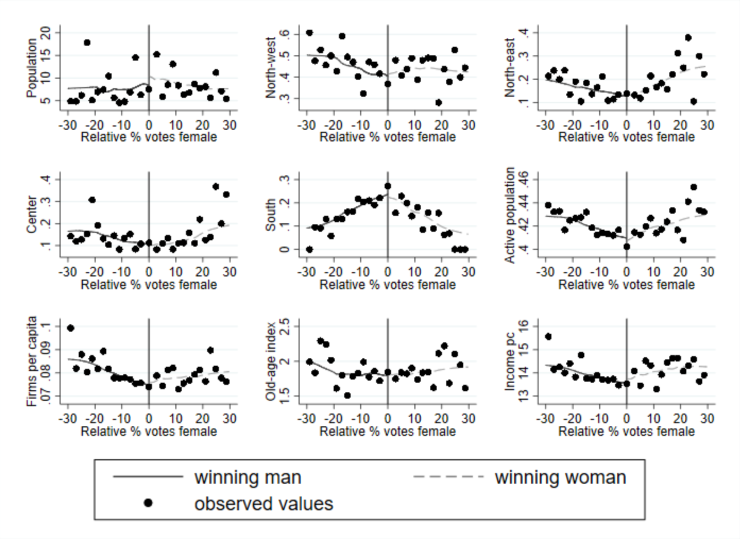
The sharp design



The running variable



Validity test



Early termination probability

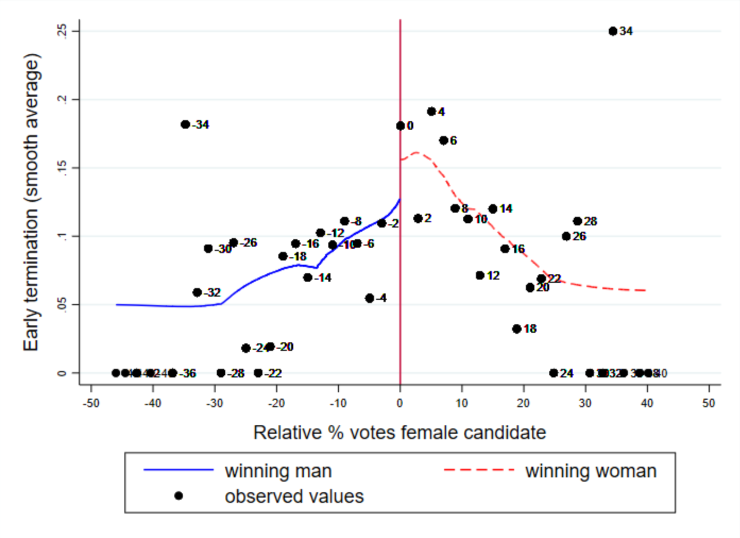


TABLE 3

The effect of mayor gender on the probability of early termination

	Coefficient on female (1) Unadjusted	Coefficient on female (2) Adjusted	Observations
Mean of the dependent variable	0·102		
Full sample			
Linear regression (whole sample)	0·017* [0·010]	0·029*** [0·009]	18,117
Linear regression with municipality fixed effects (whole sample)	0·057*** [0·019]	0·052*** [0·018]	18,117
Mixed-gender races only			
Linear regression (regression discontinuity sample)	0·043*** [0·014]	0·034** [0·014]	2313
Linear regression on both sides of discontinuity	0·073*** [0·024]	0·072*** [0·023]	2313
Two candidates, linear regression on both sides of discontinuity	0·090*** [0·034]	0·075** [0·033]	1119
Optimal bandwidth, linear regression on both sides of discontinuity	0·070*** [0·027]	0·070*** [0·025]	2085
Two candidates, optimal bandwidth, linear regression on both sides of discontinuity	0·086** [0·035]	0·070** [0·034]	1061
Half optimal bandwidth, linear regression on both sides of discontinuity	0·073** [0·036]	0·064* [0·034]	1446
Second-order polynomial on both sides of the discontinuity point	0·071** [0·033]	0·072** [0·032]	2313
Two candidates, second-order polynomial on both sides of discontinuity	0·098** [0·046]	0·084* [0·043]	1119

Heterogeneity

Effects are influenced by the proportion of women in the municipal council

Where the proportion is larger, probability of early termination of female mayors is lower

TABLE 6

Interactions between mayor's and city councilors' gender, and early termination

	OLS	RDD	OLS	RDD	OLS	RDD
	(1)	(2)	(3)	(4)	(5)	(6)
Female	0·047**	0·090**	0·132**	0·169	0·132**	0·171
	[0·023]	[0·040]	[0·058]	[0·151]	[0·058]	[0·151]
Female × Prop. female in council	−0·087	−0·149				
	[0·102]	[0·137]				
Implied effect of a female mayor at the mean of Prop. female in council	0·031***	0·089**				
	[0·010]	[0·040]				
Female × (Prop. female in council > 0)					−0·107*	−0·117
					[0·059]	[0·150]

Potential explanation: Female mayors face lower hurdles/discrimination where female presence in gov't is higher

Application # 2 – Casarico, Lattanzio, Profeta (2022)

Research question

We investigate whether male and female mayors take different decisions on the size and allocation of public spending and revenues

We study whether gender differences in fiscal policy outcomes are influenced by

- the gender composition of municipal council and executive committee
- the electoral rule according to which the mayor is elected

Data

- Data on elections and mayors of Italian municipalities over the period 2000-2015
- Municipalities' balance sheets

Application # 2 – Casarico, Lattanzio, Profeta (2022)

Empirical strategy

Identification strategy: Sharp RDD

$$Y_{it} = \alpha + \beta F_{it} + \gamma MV_{it} + \delta F_{it} \times MV_{it} + X'_{it}\pi + \eta_t + \varepsilon_{it}$$

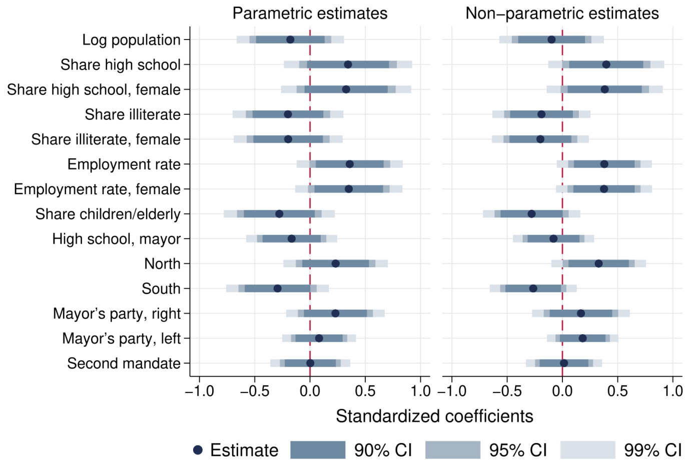
Heterogeneity analysis

1. Share of women in municipal council or executive committee
2. Electoral rule (above/below 15,000 residents)

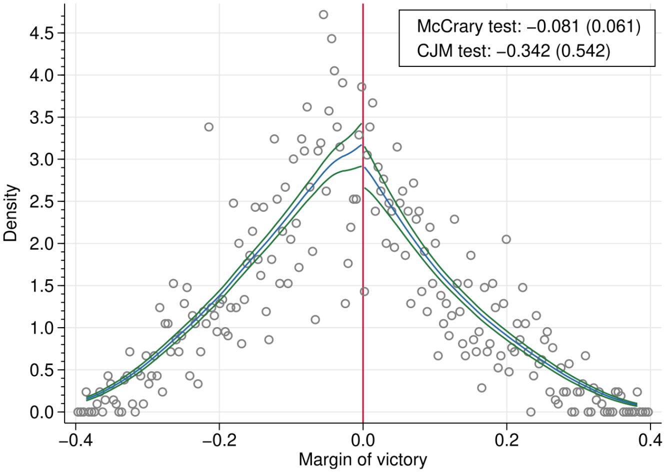
Estimating equation (within optimal bandwidth)

$$Y_{it} = \alpha + \beta F_{it} + \gamma MV_{it} + \delta F_{it} \times MV_{it} + \mu Z_{it} + \lambda F_{it} \times Z_{it} + X'_{it}\pi + \eta_t + \epsilon_{it}$$

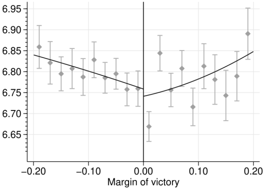
Validity tests



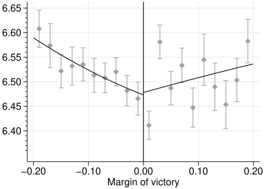
Validity tests



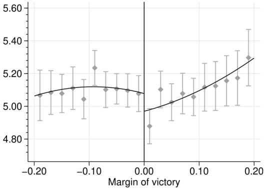
RDD – Visual representation



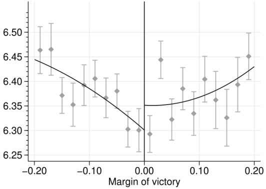
(A) Total expenditures



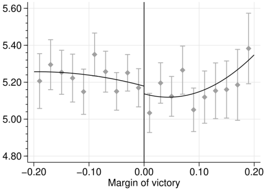
(B) Current expenditures



(C) Capital expenditures

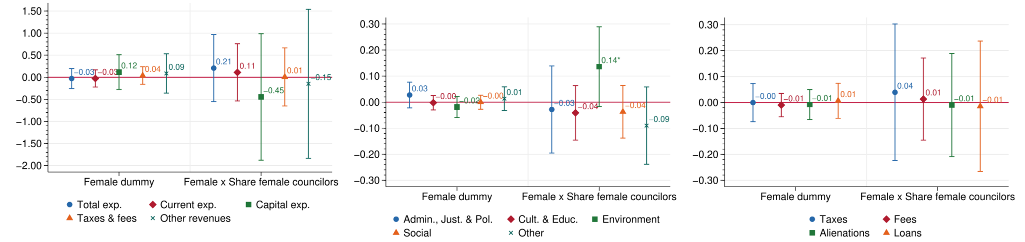


(D) Revenues from taxes and fees



(E) Other revenues

Heterogeneity by female share in municipal council



(A) Expenditure & revenue levels

(B) Expenditure shares

(C) Revenue shares

Fig. 8. Heterogeneous effects by share of women in the municipal council.
Notes. The figure reports estimates of β and λ from Eq. (3), i.e. the effect of mayor's gender in municipality with no female councilors and the interaction effect between mayor's gender and the share of female councilors, respectively, on each outcome at the cut-off. Panel A reports results for log per capita expenditures and revenues, panel B for expenditure shares and panel C for revenue shares. Vertical lines are 95 percent confidence intervals, obtained from municipality-level cluster-robust standard errors. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Application # 3 – Carta and Rizzica (2018)

Empirical strategy

- Investigate the effects of a policy intervention that caused a **sharp** reduction in the price of childcare for 2-year-olds – Early Kindergarten [EK]
- Focus on mothers' labour supply decisions: participation and employment [and on children's development]
- Running variable: age of the child
- Identifying assumption: around the age threshold affected by the reduction in price, households have similar characteristics

Application # 3 – Carta and Rizzica (2018)

Empirical strategy

- **Moratti reform**, in 2003, introduces early access to primary school and then extends same access rules to kindergarten $\rightarrow$ EK
- Shift in age of school population, w/ staggered implementation:

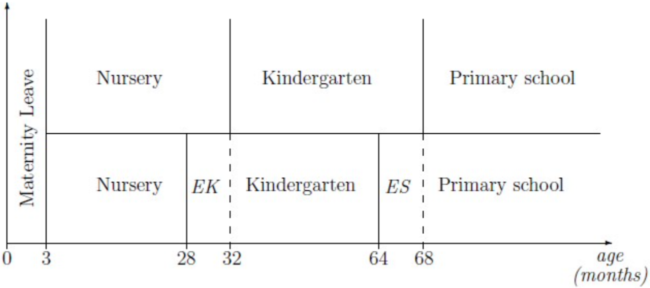
School year $t/t+1$:	Access to kindergarten, child turns 3 by:	Access to primary school, child turns 6 by:
Until 2002/2003	31 December t	31 December t
2003/2004 - 2004/2005	28 February $t+1$	28 February $t+1$
2005/2006	28 February $t+1$	31 March $t+1$
2006/2007	28 February $t+1$	30 April $t+1$
2007/2008	28 February $t+1$	30 April $t+1$
2008/2009	31 January $t+1$	30 April $t+1$
2009/2010 onwards	30 April $t+1$	30 April $t+1$

Notes: Rules are for access to kindergarten and primary school in September of school year $t/t+1$ and refer to dates of birth within the school year. The different cutoff dates for the implementation of pre-kindergarten and pre-school were indicated, on a yearly basis, by the Ministry of Education.

Application # 3 – Carta and Rizzica (2018)

Empirical strategy – The reform

Childcare services in Italy by age (in months) of the child at the beginning of the school year (1 September).



Notes: Upper panel shows the Italian childcare system *before* the Moratti reform and lower panel the one *after* the reform. EK stands for early kindergarten and ES for early school; they refer to the possibility of anticipating access to the corresponding educational stage.

Application # 3 – Carta and Rizzica (2018)

Empirical strategy – Mother's labour supply (LS)

- Assignment rule:

$$EK_{it} = \begin{cases} 1 & \text{if } dob_i \leq 30/04/t-3; \\ 0 & \text{otherwise.} \end{cases}$$

- Caveat: Intention-to-treat (ITT) effect since actual enrollment **is not** observed
- Regression Discontinuity

$$\Pr[LS_{it}] = \beta EK_{it} + f(p_i) + \epsilon_{it}$$

$$p_i = dob_i - 30/04/t - 3$$

- Treatment effect $\hat{\beta} = \tau^{RDD}$

Application # 3 – Carta and Rizzica (2018)

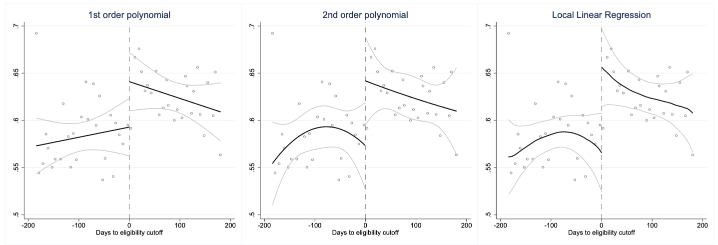
Data

- Italian Labour Force Survey
- School years: 2009/10, 2010/11, 2011/12
- Mothers aged 18-50 whose youngest child is born within 6 months from the PK eligibility cutoff date

Application # 3 – Carta and Rizzica (2018)

Results on mothers' participation

Effect of eligibility for early kindergarten on mothers' labor market participation.

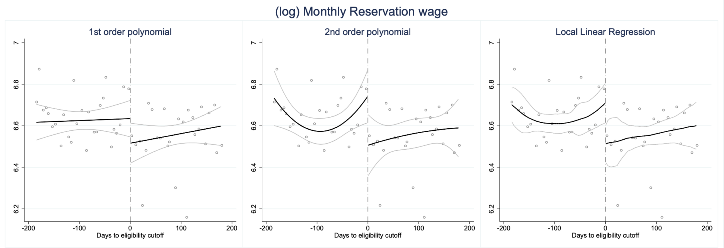


Notes: The horizontal axis shows the distance from the cut-off date of birth (p_i). Observations to the right of the cut-off correspond to children who were born *before* the cut-off (eligible for early kindergarten), observations to the left of the cut-off correspond to children who were born *after* the cut-off date (non-eligible). The graphs show the estimated discontinuity for first and second order polynomial approximations and for local linear regression with triangular Kernel weights and a bandwidth of 120 days. The gray lines are the estimated 95% level confidence intervals. The dots of the underlying scatterplots show the mean outcome in bins of one week's width.

Application # 3 – Carta and Rizzica (2018)

Results on mothers' reservation wage

Effect of eligibility for early kindergarten on (log) monthly reservation wage of unemployed mothers.



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Application # 3 – Carta and Rizzica (2018)

Results – Summing up

- **RD**: The possibility of using EK increased maternal participation by 5-7 p.p. and employment by 4.5-6 p.p.
- The effect on employment is driven by the increase in participation and by a decrease in the reservation wage (-180 euro per month, i.e. -11% to -20%)
- Effects are larger on mothers:
  - living in regions with higher job finding rate
  - married
  - living in more affluent households

References and Materials

*** = mandatory (only parts covered in class)**

- (*) Carta, F., and Rizzica, L. (2018). Early kindergarten, maternal labor supply and children's outcomes: Evidence from Italy. *Journal of Public Economics*, 158(C), 79-102

- (*) Casarico, A., Lattanzio, S., and Profeta, P. (2022). Women and Local Public Finance. *European Journal of Political Economy*, 72, 102096.

- Cunningham, S. "The Mixtape", Ch. 6, `https://mixtape.scunning.com/06-regression_discontinuity`

- (*) Gagliarducci, S. and Paserman, M. D. (2012). Gender Interactions within Hierarchies: Evidence from the Political Arena. *The Review of Economic Studies*, 79(3):1021-1052.

- Lee, D. S., and Lemieux, T. (2010). Regression Discontinuity Designs in Economics. *Journal of Economic Literature*, 48(2):281-355.