Examples: Impacts of *Comunidades Solidarias Rurales* in El Salvador and *BISP* in Pakistan

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Pakistan BISP- Fuzzy RDD evaluation

- Recently completed evaluation of unconditional cash transfer program in Pakistan, Benazir Income Support Program
- Program offers women who are in households below the poverty score threshold a 1000 rupee monthly transfer
- Program has recently expanded and now covers 6 million beneficiaries

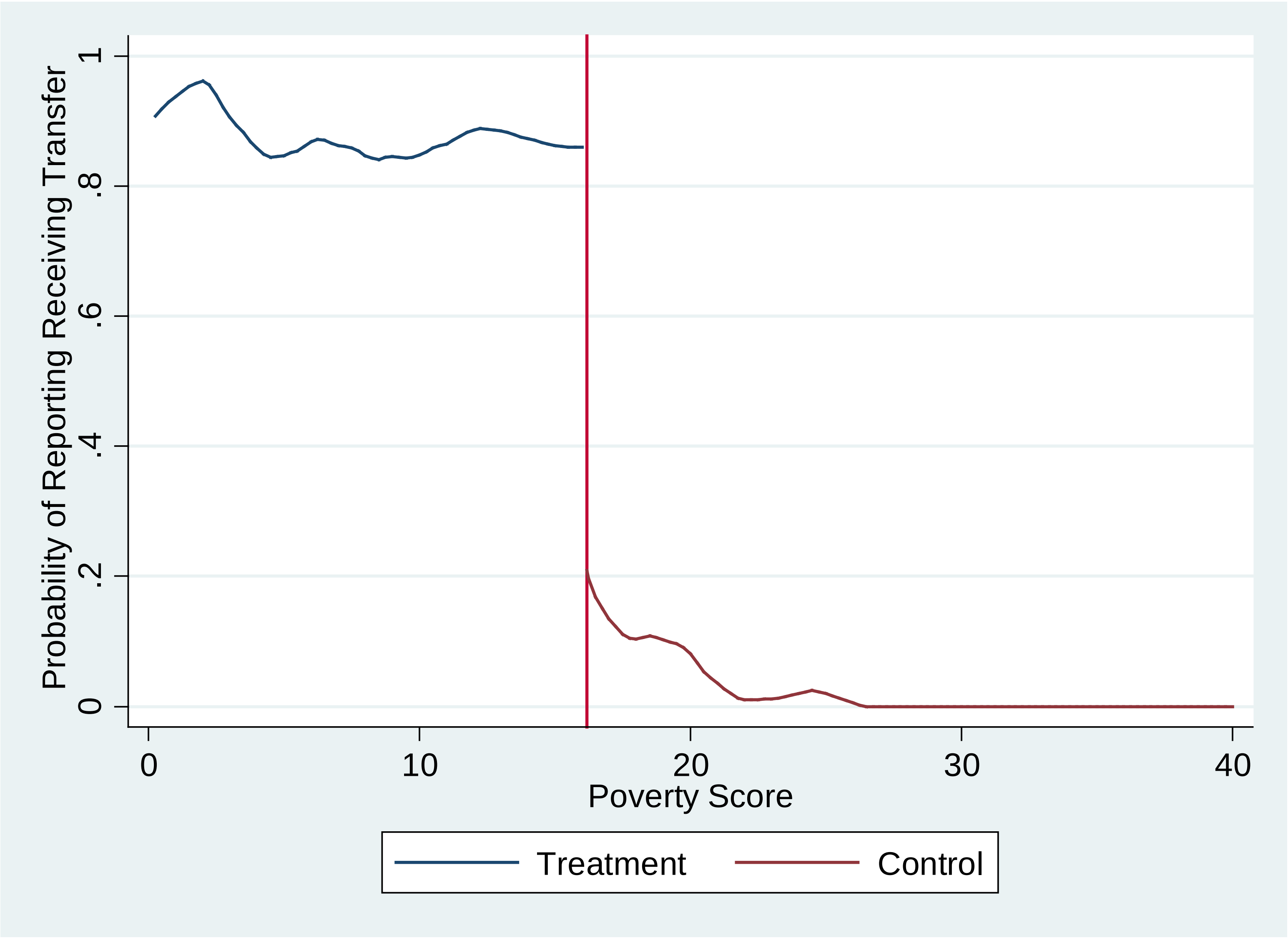
Problem: Imperfect Compliance

- Some people who should be eligible (have CNIC cards etc.) do not receive transfers
  - May just not receive transfers <u>yet</u>
- Other people who have higher scores receive the benefits
  - Several potential reasons for households to receive benefits even if ineligible

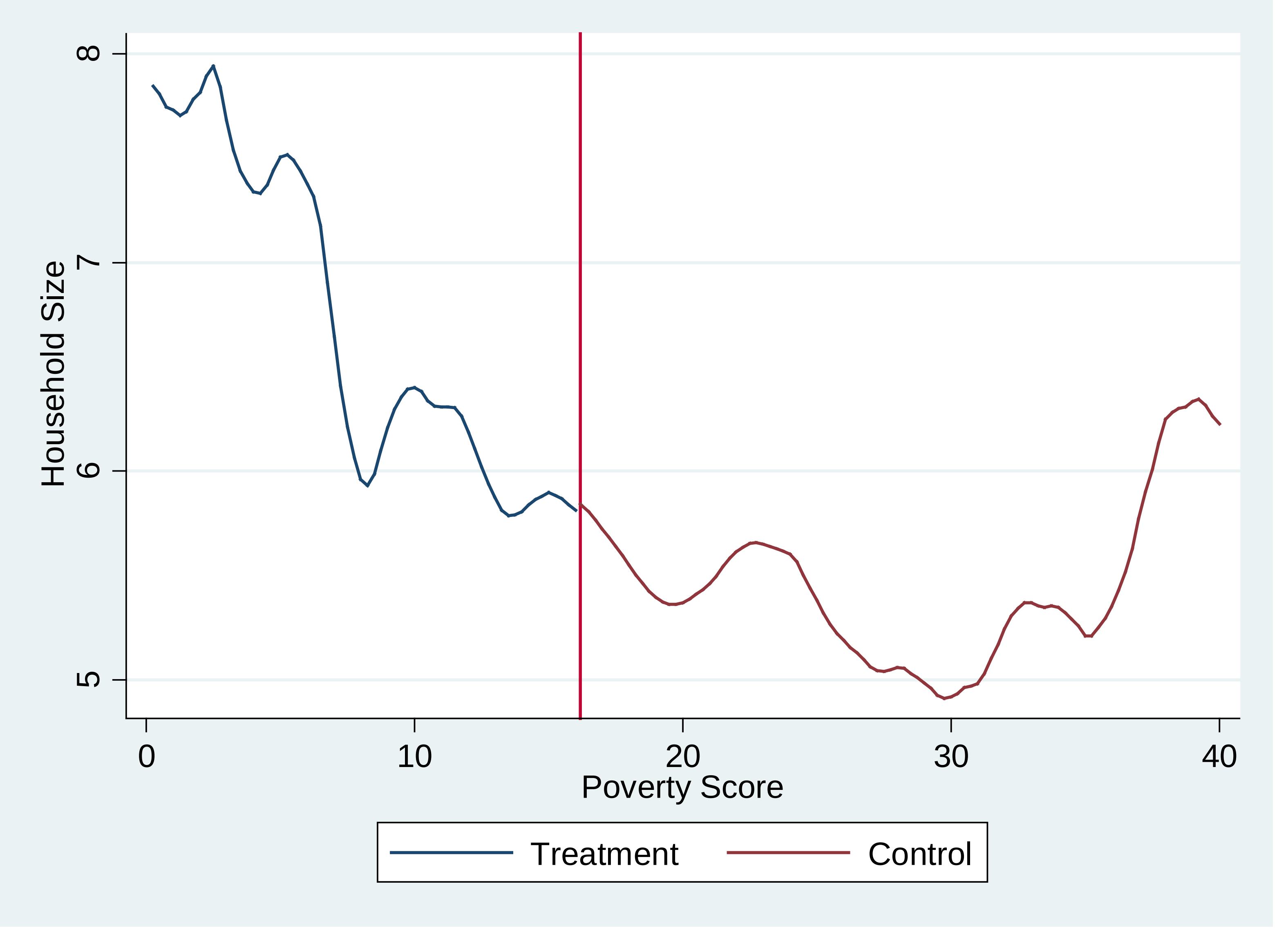
Data

- Collected by Oxford Policy Management in 2011 and 2012 (“rapid” follow-up)
  - Collected specifically for RDD- supposedly close to threshold
  - This is a panel of households
- Matched with administrative data on eligibility and poverty score
  - Implies we threw out people we could not find in admin data for RDD component of the evaluation

Discontinuity at the Threshold?



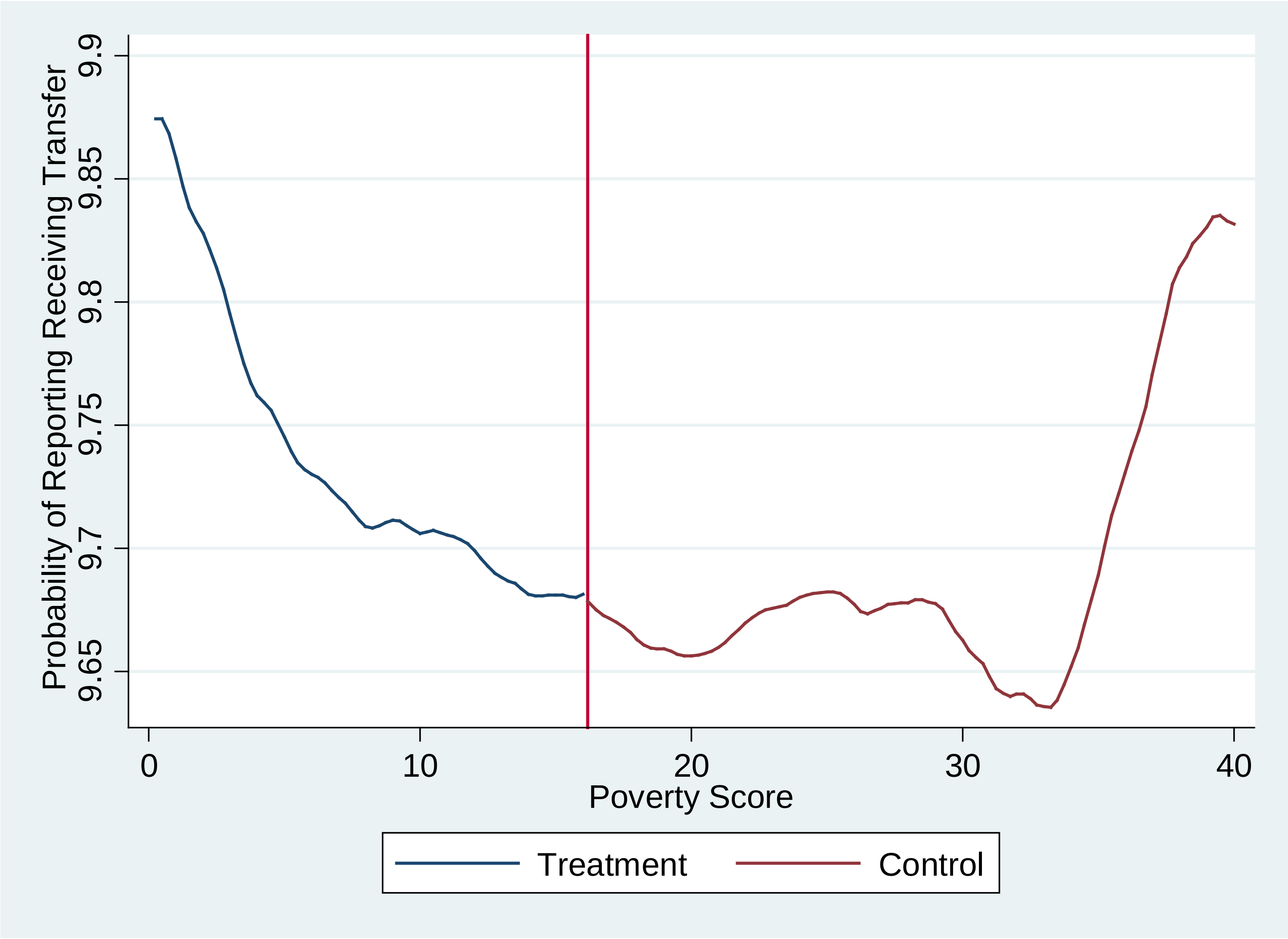
X variables continuous at threshold?



Specification of Regressions

- Can use "Wald" estimator (Nichols, 2007)
  - This is implemented with the "rd" command in Stata
- Or can use two stage least squares
  - This is effectively an IV estimator or a 2SLS estimator in which we limit the bandwidth.
  - Probably better to stick to linear in the forcing variable (at least in this case)
- Graphs can still teach you something

Example : Consumption



Summary

- We had difficulty finding significant impacts from Pakistan BISP with fuzzy RDD
  - Could be Wald estimator; noise near threshold
  - You do need larger bandwidths with fuzzy RDD (theoretically)
- Not convinced about the Wald estimator
  - Large impact estimates, too large to be believed. Should reflect graph.

Example 2

- Another CCT Evaluation
  - Red Solidaria in El Salvador
  - Story of IE design… can you use matching when there is a variable or are variables that completely explain program participation?

Example: Impacts of *Comunidades Solidarias Rurales* in El Salvador

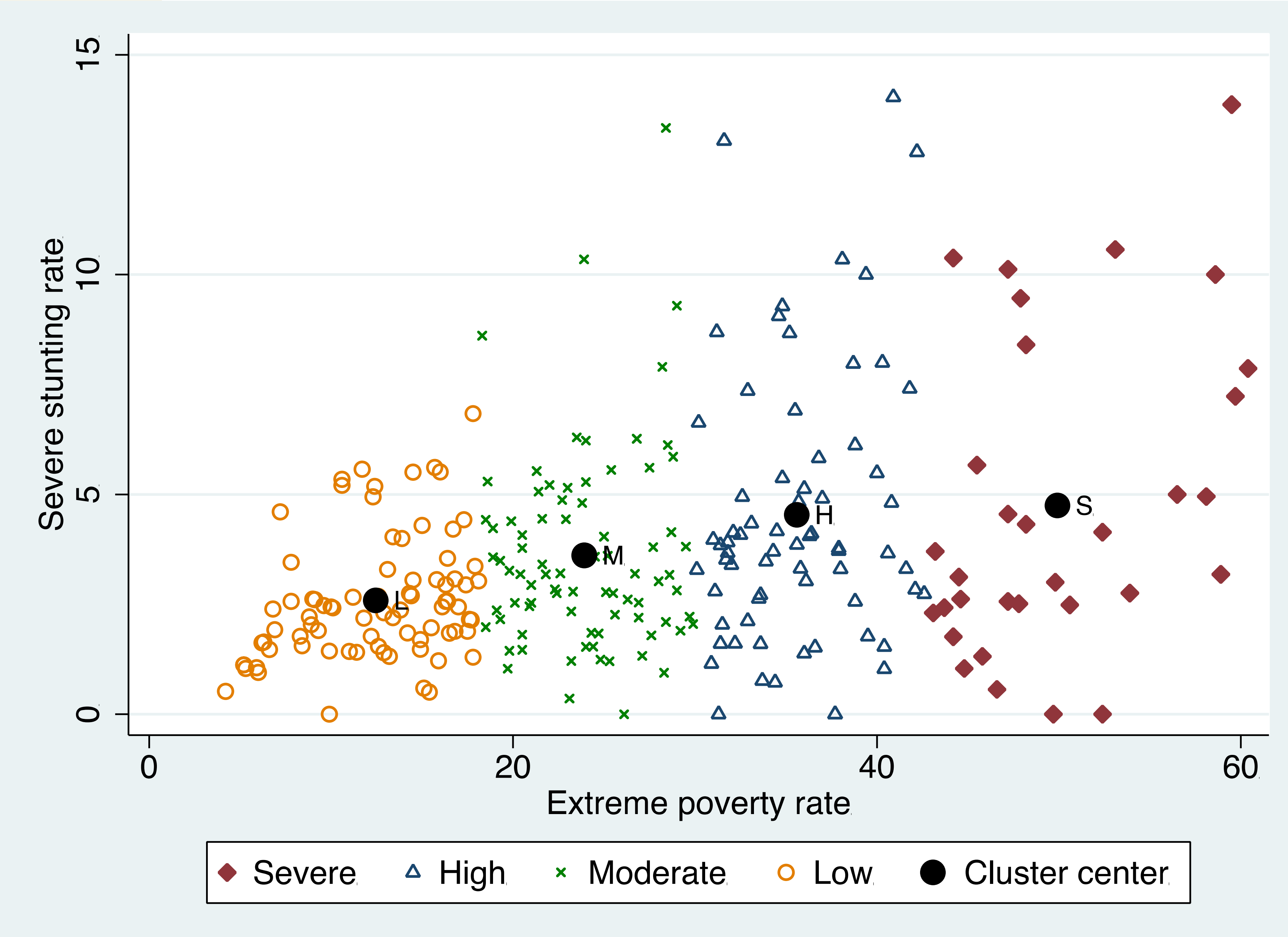
- CSR was designed to reduce poverty in the poorest rural areas of El Salvador
- Similar to other CCTs in Latin America (e.g. Progresa, Bolsa Familia)
- Targeted Categorically and Geographically in El Salvador
  - **Health Targeting**: Children under 5 (growth monitoring, vaccinations)
  - **Educational Targeting**: Children aged 6 to 15 (18) who have not completed primary school

Geographic Targeting

- Took place in two stages
- Geographic Targeting: Used two poverty indicators to cluster municipios into four "extreme poverty" groups
- Indicators
  - Poverty Rate, measured at *municipio* level
  - Severe Stunting Rate in first grade census (2000)

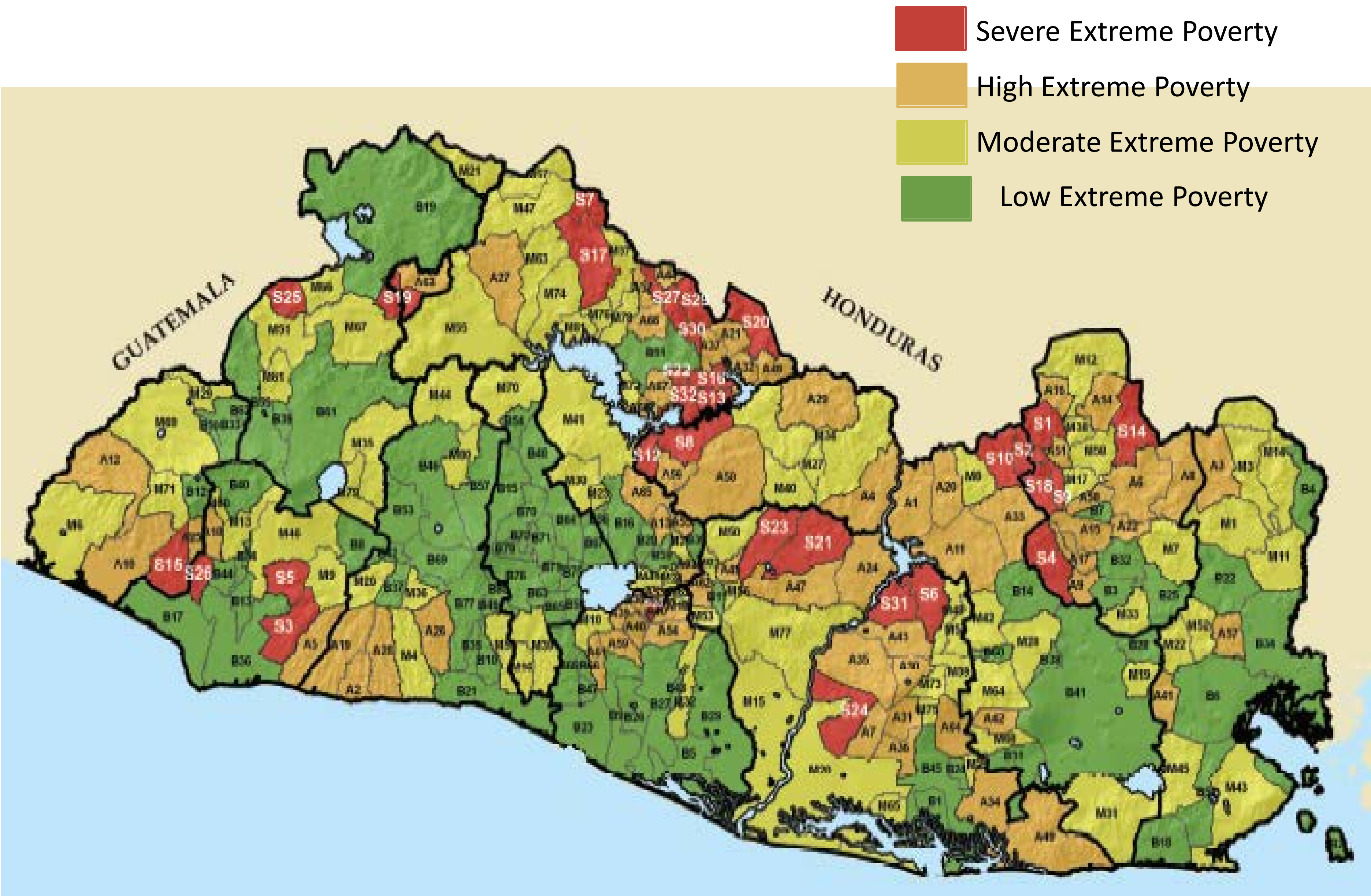
Targeting (cont.)

- Used *partitioned cluster analysis* for grouping
  - Severe, High, Moderate, Low groups (S, A, M, B in following graph)
- **No** other targeting– everyone in the rural areas of *municipios* were eligible for the *bono* (conditional on children in an eligible group being present)



Severe stunting rate
Extreme poverty rate
0
5
10
15
0
20
40
60
L
M
H
S
Severe
High
Moderate
Low
Cluster center

GEOGRAPHIC TARGETING:
MAP OF EXTREME POVERTY, EL SALVADOR



Implementation of Program

- Took place over five years
- Poorest groups entered first (severe PG, in 2005 and 2006)
  - Sequentially entered by Municipality Marginality Index (IIMM)
- Next poorest *municipios* entered sequentially (2007-2009)
  - Also entered sequentially by IIMM
- To compare 2006 with 2007 entry groups, need to use poverty rates and severe stunting rate as a "forcing variable"

Education *Bono*

- Paid to all households with children aged 6-15 (18 after 2008) who were:
  - Household members;
  - Enrolled in school if primary school (grade 6) not complete;
  - Attending more than 80% of the time.
- *Bono* is \$15/month if household only eligible for education *bono*; \$20/month if both education and health
  - Does not vary by number of children

Estimating Impacts of CSR on school enrollment

- Poorest two groups-- severe and high extreme poverty-- targeted for transfers
  - Order of entry into program determined by a ranking within extreme poverty group (Municipality Marginality Index)
- We examine impacts between 2006 and 2007 entry group

Why compare 2006 and 2007 entry groups?

- RDD is a local impact estimator, and ideally estimate impacts among poorest possible group
- Cannot use 2005 and 2006 (no available data)
- Additional advantage– 2007 Census Data
  - Because conditionality not implemented in first partial year of program, 2007 school year is first conditional year of program in 2006 entry group

Implicit Partition

- Partitioned Cluster Analysis defines cluster “centers” using a measure of distance from the cluster center
  - Analyst initially decides number of clusters and initial centers
  - Final clusters in iterative process leads to clusters that have multiple indicators closest to one another
- For any two cluster centers, there exists a set of points that are equidistant from the two cluster centers
  - Could use Euclidean distance, or another distance measure

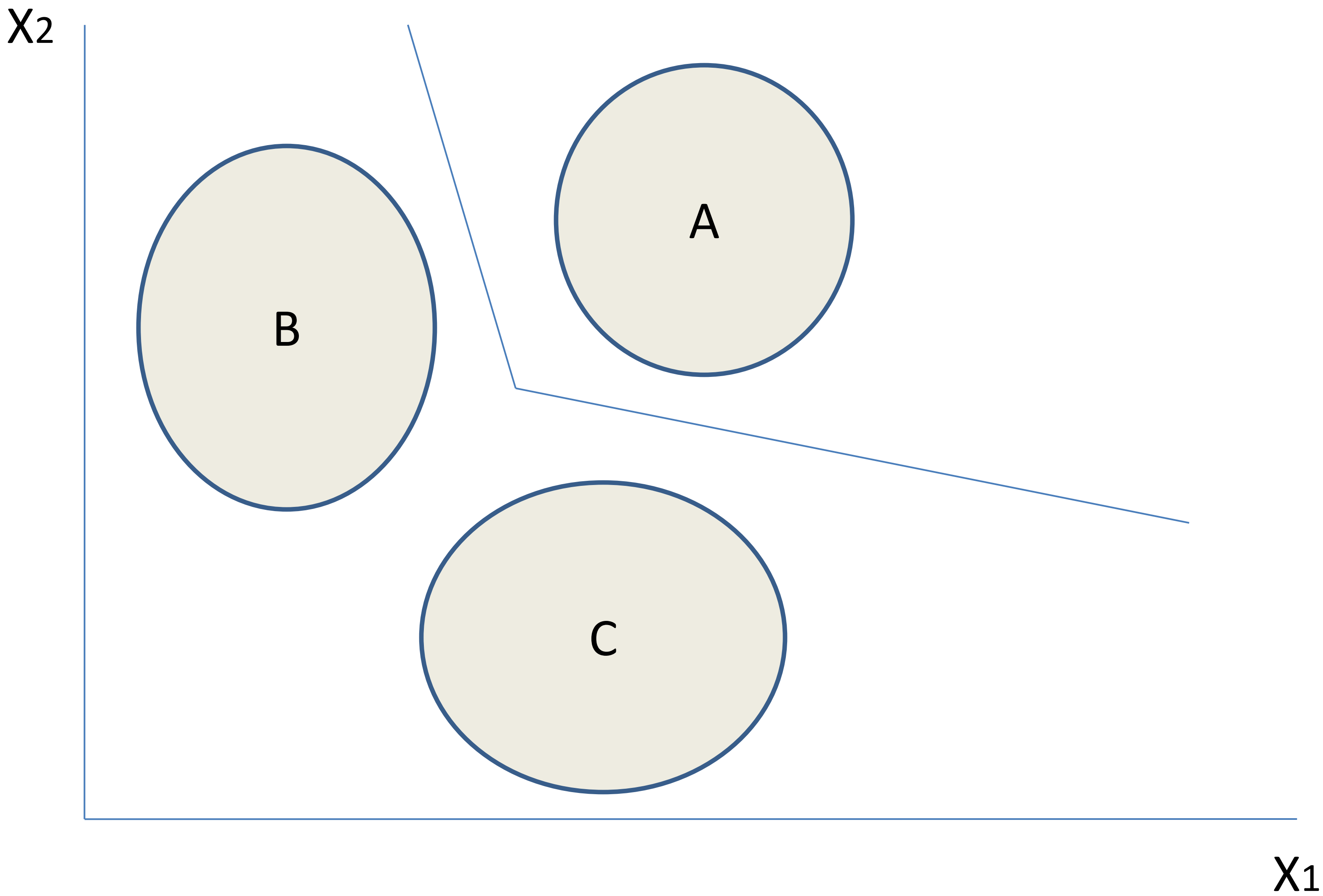
Estimating RD using distance as implicit partition

- Assign *A* clusters as treatment clusters, and *B* clusters as control clusters
- Boundaries or sets of equidistant points exist between all treatment and control centers
- Calling centers T, we can define a set of points closest to specific cluster centers as:

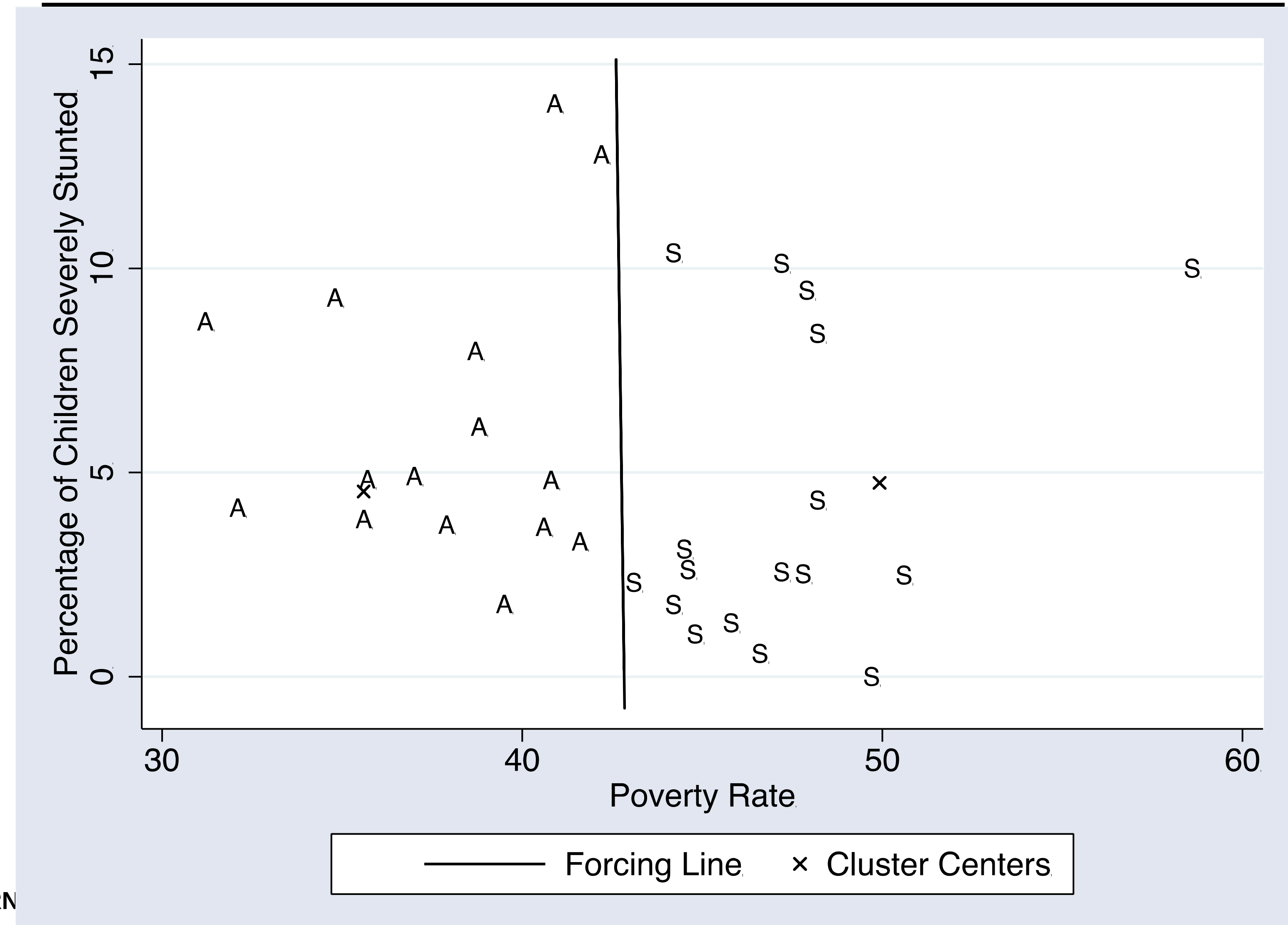
$$\min_{a \in A} d(Z_j, T_a) = \min_{b \epsilon B} d(Z_j, T_b)$$

The implicit solution to the above equation must be unique and continuous for a partition to exist.

Illustration of Estimator



2006 vs 2007 comparison groups

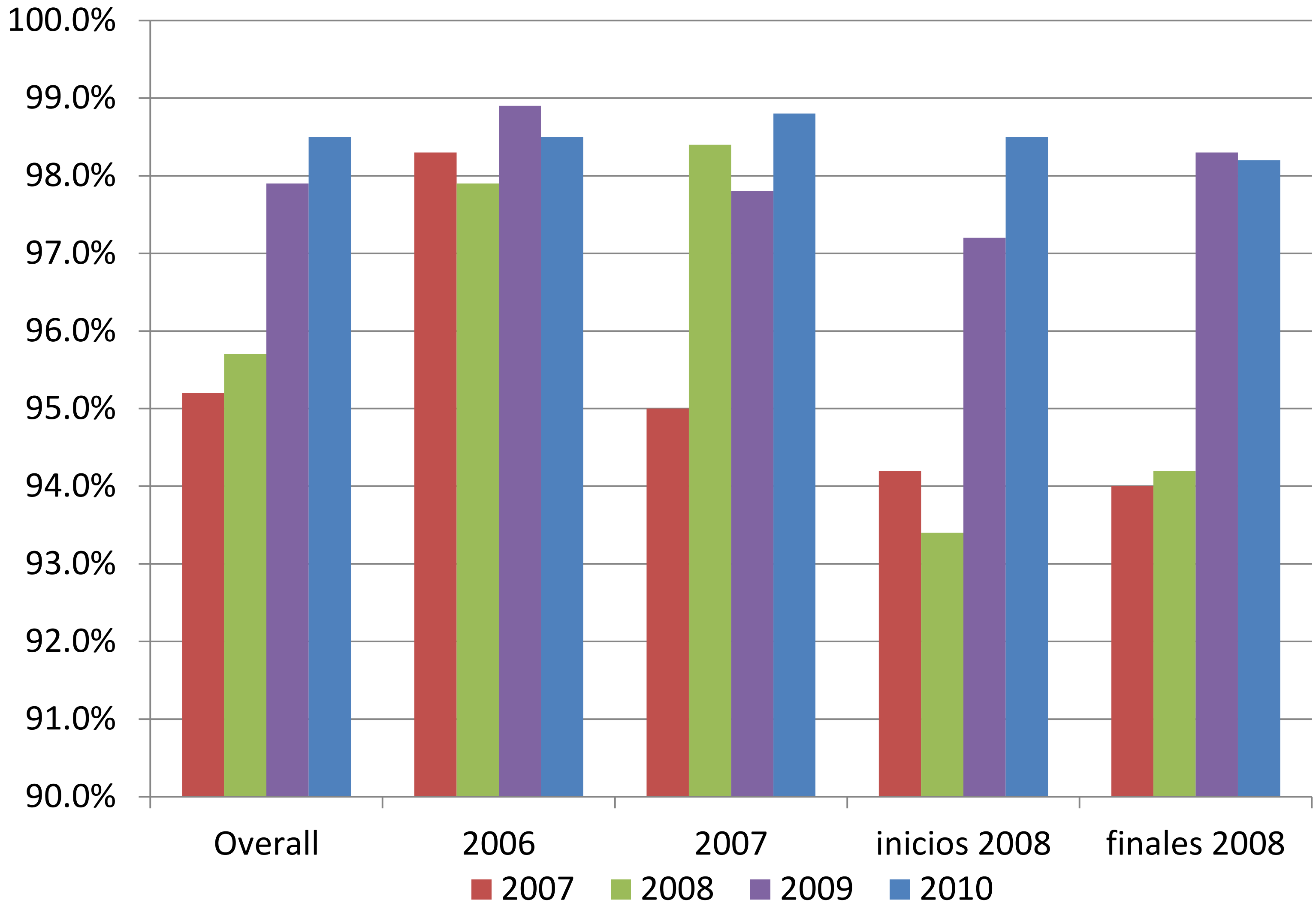


IFPRI INTERN

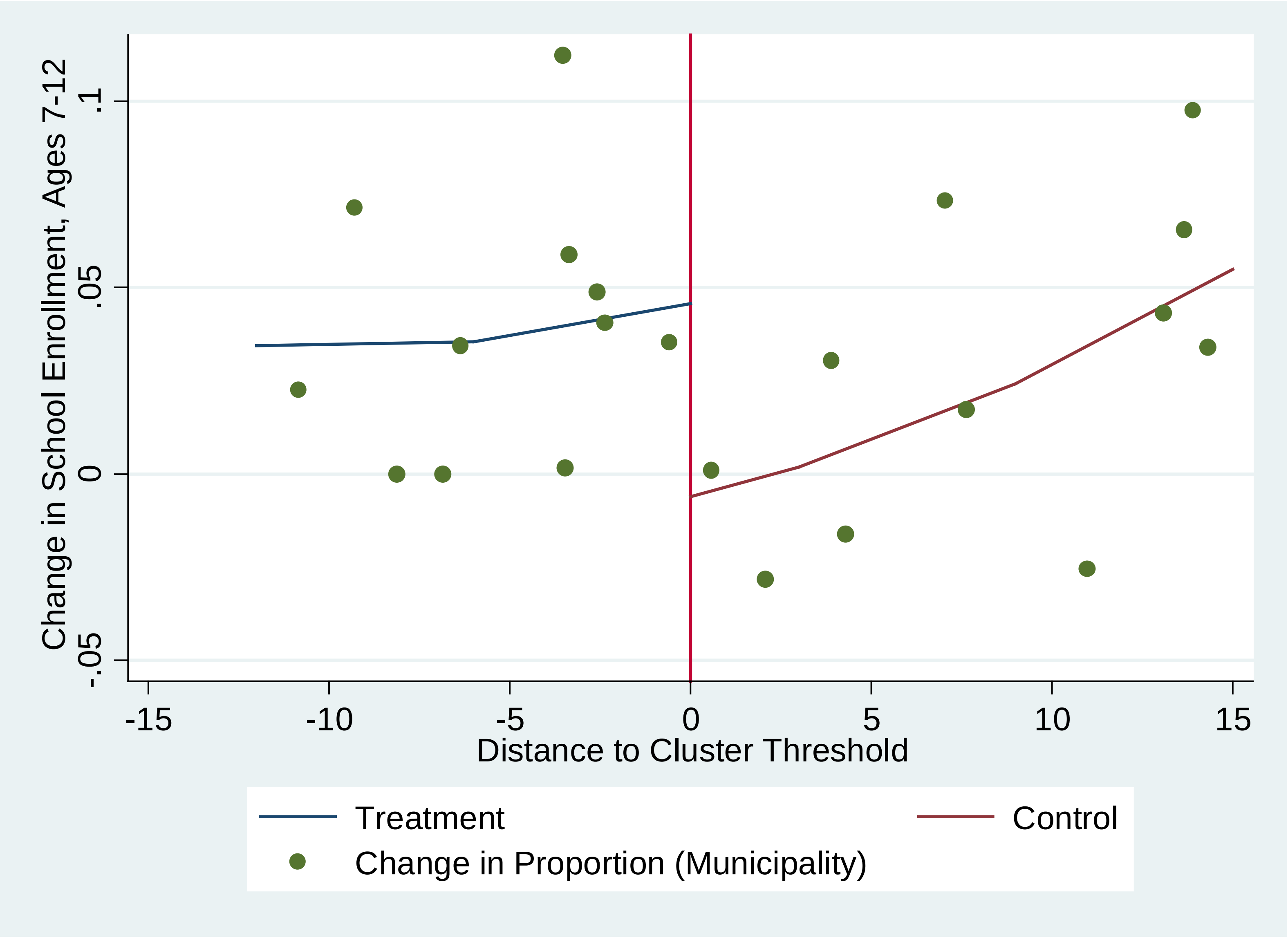
Data Sets

- First, use data set collected by IFPRI and FUSADES in early 2008 for purposes of evaluating impacts of CSR
  - Collected education “history” of the past 3 years on all children aged 4 to 18 at the time of the survey
  - Particularly interested in children aged 7 to 12 in specific years (of primary school age in El Salvador)
  - Potential problem– not truly panel data
- Second source: 6^{th} Population Census of El Salvador, conducted in May 2007
  - Includes school enrollment status
  - Can estimate by age and gender groups

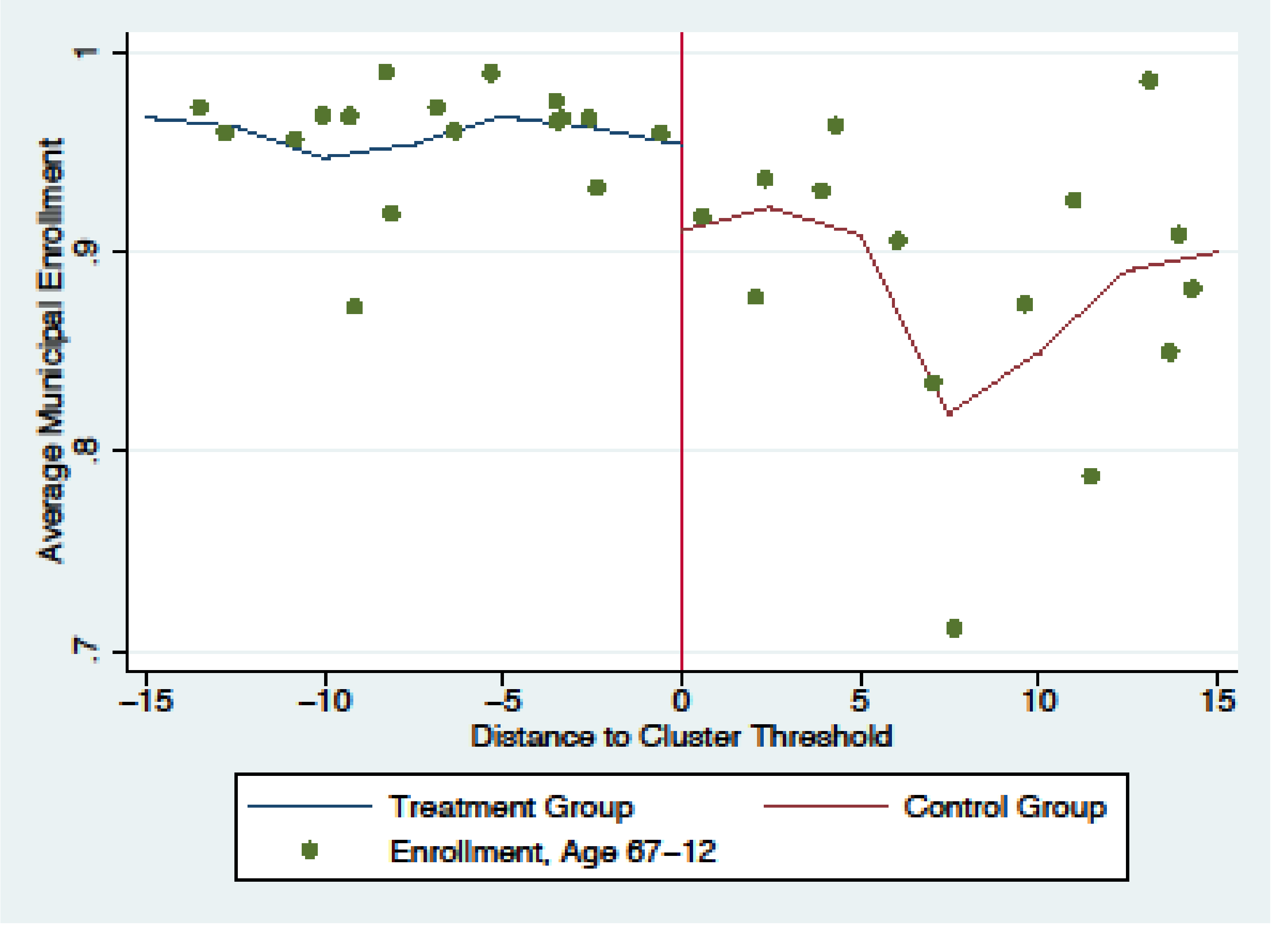
Enrollment Rates, IFPRI Evaluation Data



Results (IFPRI data)



Impact Estimates, School Enrollment

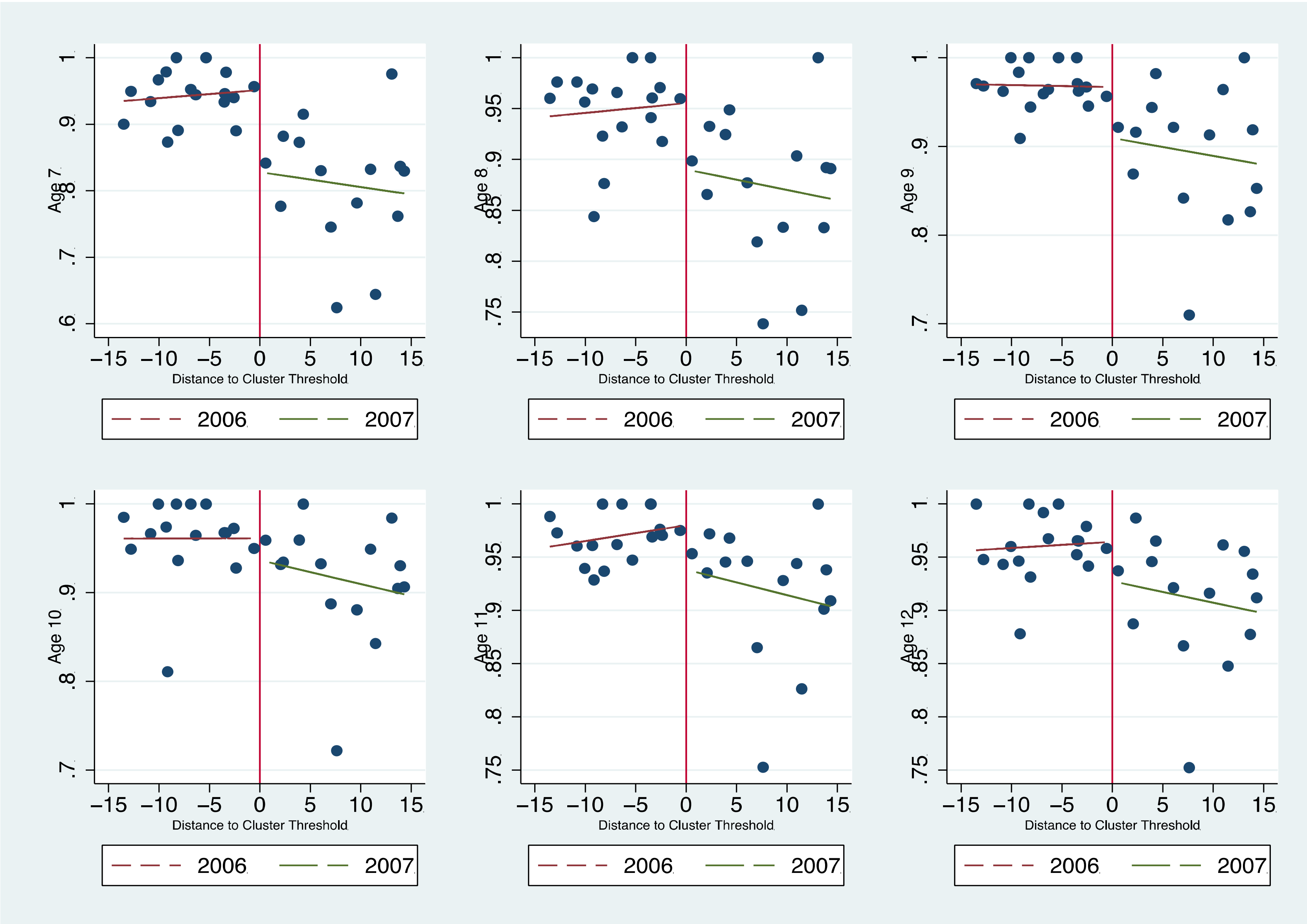


Results (All Obs. And Narrow Bandwidth)

	All observations		**Narrow Bandwidth (h=5)**	
	OLS	LLR	OLS	LLR
Impact on Enrollment	0.015	0.066	0.052	0.047
	(0.019)	(0.028)**	(0.023)**	(0.037)

Other estimation methods (Gaussian kernel; Epanechnikov kernel) also significant with narrow bandwidth

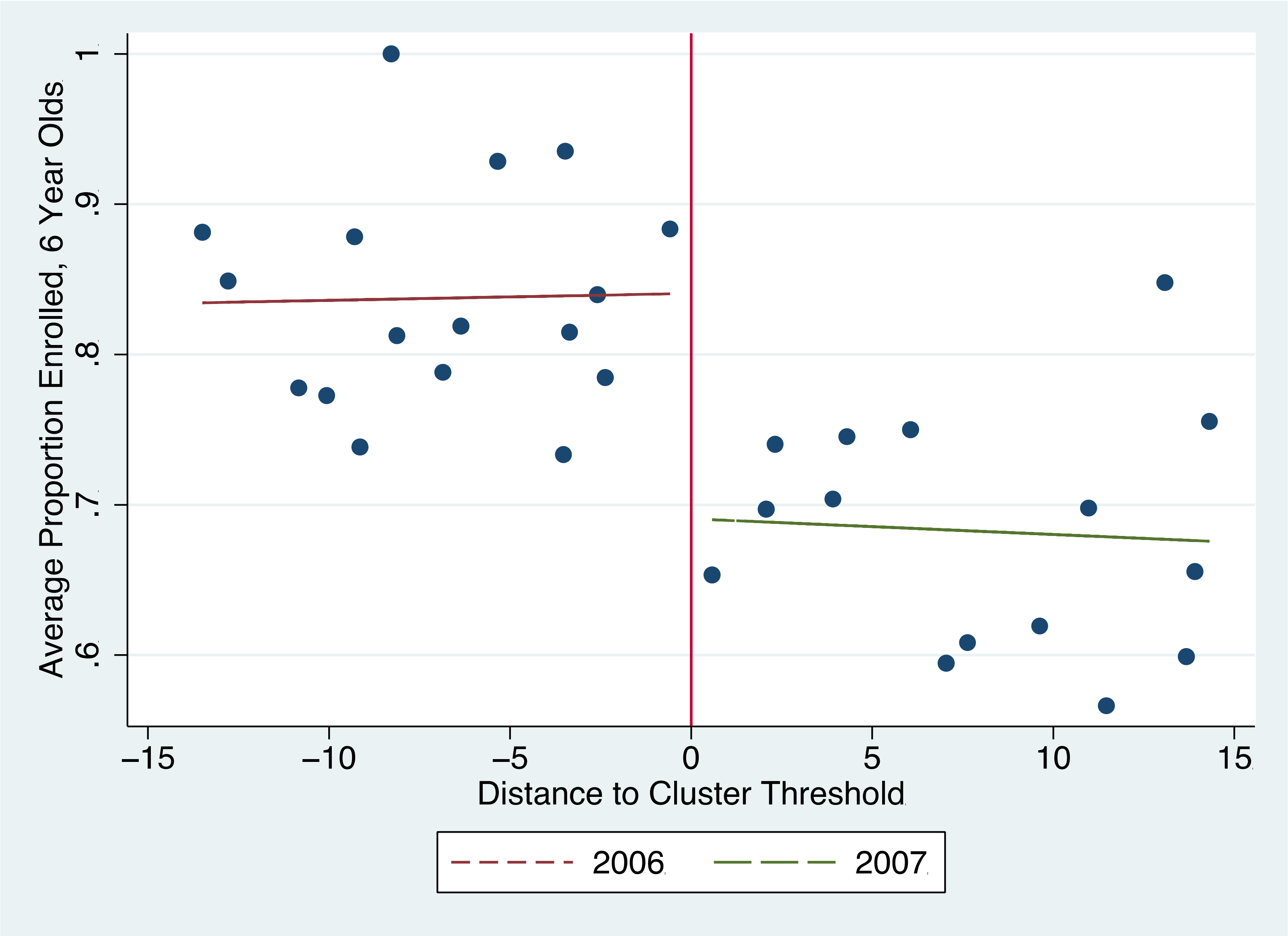
Impact Estimates on School Enrollment by Age



Impact Estimates, by gender and age

Age	All	Boys	Girls
7	0.098 (0.046)**	0.117 (0.035)**	0.074 (0.067)
8	0.054 (0.024)**	0.051 (0.026)*	0.058 (0.024)**
9	0.040 (0.019)*	0.033 (0.010)**	0.060 (0.026)**
10	-0.019 (0.021)	0.001 (0.021)	-0.048 (0.023)*
11	0.015 (0.011)	0.018 (0.009)*	0.067 (0.019)**
12	0.023 (0.017)	0.014 (0.011)	0.047 (0.021)**

Impact Estimates, 6 year olds



Impact estimates, 6 year olds

	All	Boys	Girls
Estimate	0.148	0.135	0.162
	(0.029)**	(0.058)**	(0.033)**
Number of Obs.	2509	1294	1209

Additional Impacts using Census Data

Primary Activities

- Studying
  - Positive impact overall;
  - Especially among 12-13 year olds
- Housework
  - Negative and significant, 5.9 pp overall
  - 9 pp among 12 yr old boys; 11 pp among 12 yr old girls
  - Also negative, significant impacts among 13, 14 yr old girls (smaller in magnitude)

Test Scores

- We also obtained a database of average test scores at school level on a national basis
- Can compare schools with students in RS with those who are not
- NOT causal impacts, just a regression suggesting correlations

Results, 2005 to 2008

	Grade 3		Grade 6	
Entry Group	Avg. Math Score	Avg. Lang. Score	Avg. Math Score	Avg. Lang. Score
Group 1	0.121	0.207	0.450	0.506
	(0.114)	(0.144)	(0.131)**	(0.143)**
Group 2	0.103	0.101	0.115	0.171
	(0.081)	(0.098)	(0.123)	(0.092)*
Group 3	0.036	0.094	0.068	0.147
	(0.075)	(0.087)	(0.095)	(0.103)

Summary (in numbers)

- CSR had impact of about five percentage points on school enrollment of children aged 7-12
  - Impacts are concentrated among younger children (and older girls, not shown here)
- Among children too young to be in primary school (parvularia), impacts close to 15 percentage points

Other impacts

- De Brauw and Peterman (2011) find that CSR improved maternal health outcomes around the time of birth (births attended by qualified personnel;
  Births in hospitals)
- Also apparent impacts on anthropometric measures among young children (still working on a paper)