

Economics 270c
Development Economics

Lecture 12 – April 10, 2007

Lecture 1: Global patterns of economic growth and development (1/16)

The political economy of development

Lecture 2: Inequality and growth (1/23)

Lecture 3: Corruption (1/30) – Guest lecture by Ben Olken

Lecture 4: History and institutions (2/6)

Lecture 5: Democracy and development (2/13)

Lecture 6: Ethnic and social divisions (2/20)

Lecture 7: Economic Theories of Conflict (2/27)

Lecture 8: War and Economic Development (3/6)

Human resources

Lecture 9: Human capital and income growth (4/3)

★ Lecture 10: Increasing human capital (4/10)

Lecture 11: Health and nutrition (3/13)

Lecture 12: The Economics of HIV/AIDS (3/20)

Lecture 13: Labor markets and migration (4/17)

Lecture 14: Environment and development (4/24)

Lecture 15: Social Learning and Technology Adoption (5/1)

- I will pass back graded problem set #1's next week
- I will pass out problem set #2 later this week, and it will be due to in two weeks (one week later than is listed on the syllabus)
- Please come by my office hours to discuss your 7-8 page research proposal (due May 8th). Only about half of you have stopped by so far

Lecture 12 outline

- (1) Human capital in economic development
- (2) Angrist and Lavy (1999) on pupil-teacher ratio in Israel
- (3) Banerjee, Cole, Duflo, and Linden (2006) on schooling experiments (remedial teacher, computer assisted learning) in India
- (4) Kremer, Miguel, and Thornton (2007) on girls' scholarships in Kenya

(1) Human capital in economic development

- Last week: what is the return to schooling in less developed countries?
- This week: which inputs lead to more educational production? What does the education production function look like?
- In many poor countries, education spending is the largest single recurrent discretionary budget expenditure item. E.g., in Ghana in the late 1990s, education was 35% of discretionary expenditures

(1) Human capital in economic development

- Educational production H for student i in school j could be a product of multiple factors, including a vector of individual (or household characteristics) X_{ij} , a vector of characteristics of classmates $X_{-i,j}$, and school characteristics / inputs Z_j :

$$H_{ij} = F(X_{ij}, X_{-i,j}, Z_j)$$

- For concreteness, let X_{ij} be student effort, let $X_{-i,j}$ be the “quality” of peers, and Z_j be the pupil-teacher ratio
- Parameter values could differ across populations, and complicated interactions are possible

(1) Human capital in economic development

- There are likely to be many unobserved (*) components along all three dimensions:

$$H_{ij} = F(X_{ij}^*, X_{-i,j}^*, X_{-i,-j}^*, Z_{ij}^*, Z_{-i,j}^*, Z_{-i,-j}^*)$$

- The omitted variable bias between inputs, say, and school performance could go either way. Imagine the key omitted variable (X_{ij}^*) is parent interest in education.
- Areas with “better” parents could both have greater school inputs and unobserved home educational inputs → positive bias. Or poor performing areas could be targeted for extra government transfers → negative bias

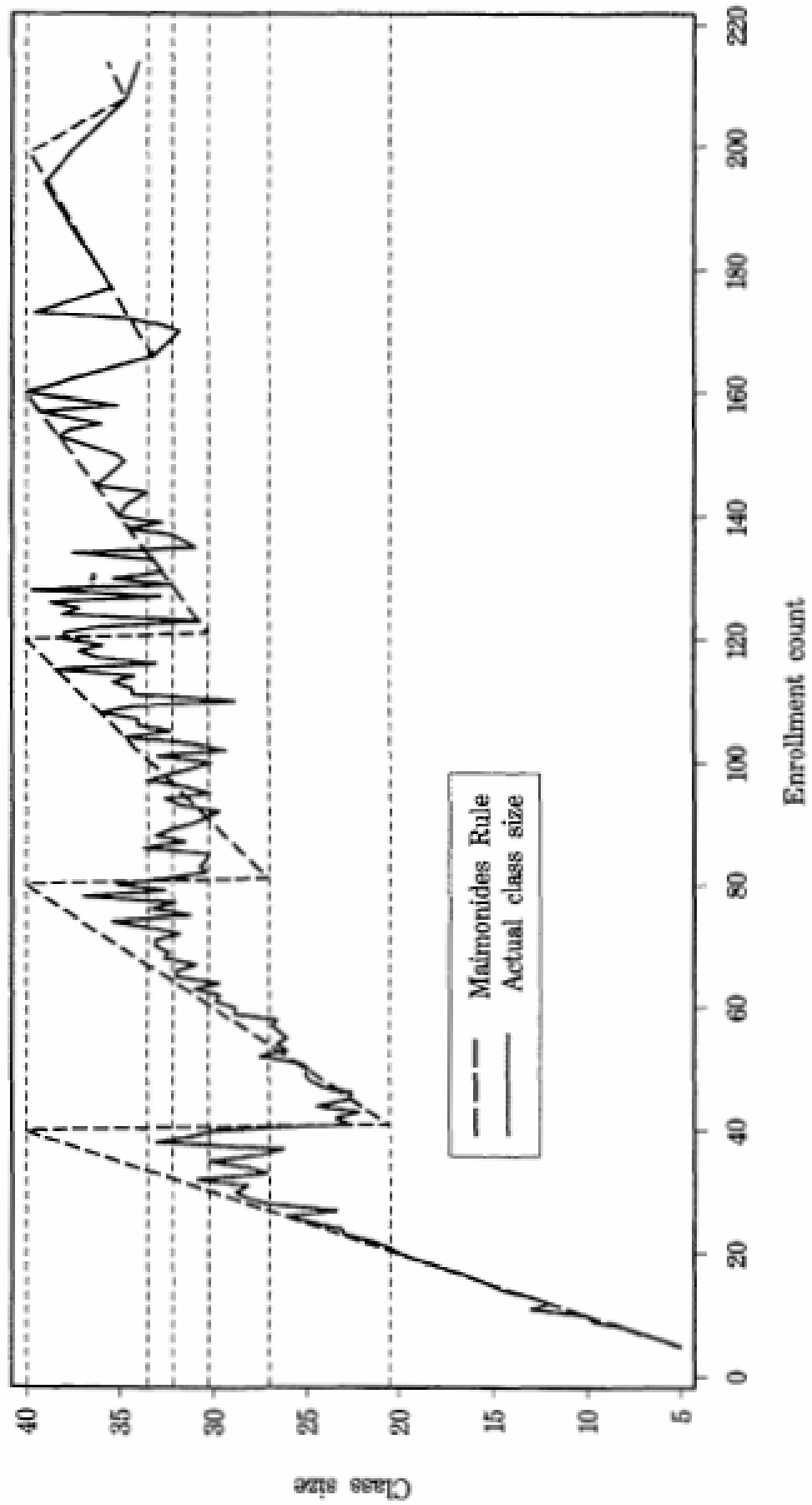
(2) Angrist and Lavy (1999)

- Class size and test score performance in Israel
- Class size based on “a rule of 40” developed by Maimonides, a 12th century Jewish-Spanish philosopher
 - I.e., up to 40 students get one teacher, 41-80 students get 2 teachers, 81-120 get 3 teachers, etc.
 - Rule introduced into Israeli schools in 1969

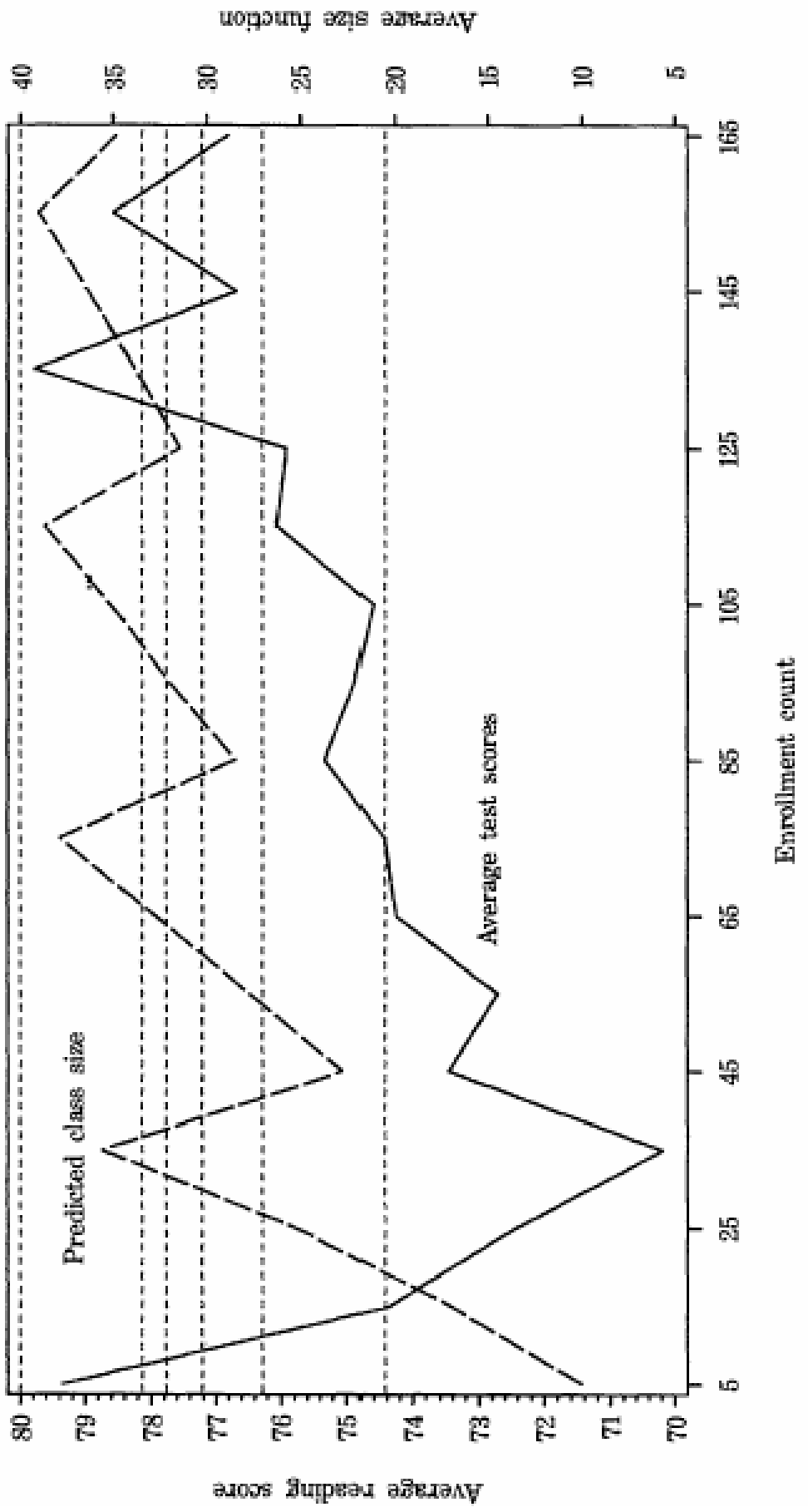
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 - I.e., up to 40 students get one teacher, 41-80 students get 2 teachers, 81-120 get 3 teachers, etc.
 - Rule introduced into Israeli schools in 1969
- Introduces sharp discontinuities in class size across otherwise similar schools. What impact on test scores in grades 4 and 5?

a. Fifth Grade



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- Main results:
- Reducing class size by ten pupils increases test scores on average by 0.25 standard deviations – a large effect
- Larger impacts on math tests than on language scores

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- Main results:
- Reducing class size by ten pupils increases test scores on average by 0.25 standard deviations – a large effect
- Larger impacts on math tests than on language scores
- Robust to many controls, restricting attention to the “discontinuity sample” near thresholds
- Largest effects for disadvantaged students (Jewish students of Sephardic / Middle Eastern origin)

(3) Banerjee et al. (2006)

- Remedial teaching (“balsakhi”), computer assisted learning, and test scores in India (Vadodara, Mumbai)
- Several other recent papers (e.g., Miguel and Kremer 2004) find large increases in school participation do not translate into test score gains. Can inputs have an impact? Or are more fundamental institutional / incentive reforms necessary? E.g., vouchers, scholarships, etc.

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- Learning per se is a major issue in India: most children are now in school but 44% of children 7-12 years old cannot read a basic paragraph (2005)

(3) Banerjee et al. (2006)

- Large positive impacts of both programs on learning in the short-run (remedial education 0.14-0.28 standard deviations, computer learning 0.21 s.d.), especially among the low performing students targeted with the remedial class.
- But small / no effect one year after programs ended

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 - But small / no effect one year after programs ended
- The remedial education findings echo some results in Angrist and Lavy (1999), e.g., larger math results
- The computer learning results differ from papers from rich countries, which tend to find smaller impacts

Table III presents the results, for various years, cities and grades from a specification which regresses the change in a student's test score (post-test score minus pre-test score) on the treatment status of the child's school-grade, controlling for the pre-test score of child i in grade g and school j :

$$(1) \quad y_{igj}POST - y_{igj}PRE = \lambda + \delta D_{jg} + \theta y_{igj}PRE + \epsilon_{igj}POST,$$

where D_{jg} is a dummy equal to 1 if the school received a balsakhi in the child's grade g , and 0 otherwise.⁹ This specification asks whether children improved more, relative to what would have been expected based on their pre-test score, in treatment schools than in comparison

Table II: Test Score Summary Statistics for Balsakhi and CAL Programs

	PRE TEST				POST TEST					
	Treatment	Comparison	Difference	Treatment	Comparison	Difference	Treatment	Comparison	Difference	
	(1)	(2)	(3)	(4)	(5)	(6)	(4)	(5)	(6)	
A. Balsakhi Modara										
Year 1 (Grades 3 and 4)	Math	-0.007	0.000	-0.007 (0.059)	0.348	0.171	0.177 (0.070)	0.348	0.171	0.177 (0.070)
	Language	0.025	0.000	0.025 (0.061)	0.794	0.667	0.127 (0.076)	0.794	0.667	0.127 (0.076)
Year 2 (Grades 3 and 4)	Math	0.046	0.000	0.046 (0.053)	1.447	1.046	0.401 (0.078)	1.447	1.046	0.401 (0.078)
	Language	0.055	0.000	0.055 (0.058)	1.081	0.797	0.285 (0.071)	1.081	0.797	0.285 (0.071)
B. Balsakhi Modara										
Year 1 (Grade 3)	Math	0.002	0.000	0.002 (0.108)	0.383	0.227	0.156 (0.126)	0.383	0.227	0.156 (0.126)
	Language	0.100	0.000	0.100 (0.108)	0.359	0.210	0.149 (0.102)	0.359	0.210	0.149 (0.102)
Year 2 (Grades 3 and 4)	Math	-0.005	0.000	-0.005 (0.058)	1.237	1.034	0.203 (0.107)	1.237	1.034	0.203 (0.107)
	Language	0.056	0.000	0.056 (0.054)	0.761	0.686	0.075 (0.061)	0.761	0.686	0.075 (0.061)
C. Cojar Assisted Learning Modara										
Year 2 (Grade 4)	Math	-0.054	0.000	-0.054 (0.076)	1.129	0.810	0.319 (0.087)	1.129	0.810	0.319 (0.087)
	Language	-0.009	0.000	-0.009 (0.083)	0.719	0.709	0.010 (0.093)	0.719	0.709	0.010 (0.093)
Year 3 (Grade 4)	Math	0.125	0.000	0.125 (0.073)	0.813	0.232	0.581 (0.089)	0.813	0.232	0.581 (0.089)
	Language	0.116	0.000	0.116 (0.079)	0.118	0.014	0.104 (0.080)	0.118	0.014	0.104 (0.080)

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Table III: Estimates of the Impact of the Balsakhi Program, by City and Sample

	Number of Observations	Dependent Variable: Test Score Improvement (Posttest - Pretest)		
		Math (1)	Language (2)	Total (3)
A. Pooling Grades and Locations				
Mumbai and Vadodara Together Year 1	12855	0.182 (0.046)	0.076 (0.056)	0.138 (0.047)
Mumbai and Vadodara Together Year 2	21936	0.353 (0.069)	0.187 (0.050)	0.284 (0.060)
B. Pooling Both Grades				
Vadodara Year 1	8426	0.189 (0.057)	0.109 (0.057)	0.161 (0.057)
Vadodara Year 2	11950	0.371 (0.073)	0.246 (0.061)	0.331 (0.070)
Mumbai Year 1 (Grade 3 Only)	4429	0.161 (0.075)	0.086 (0.066)	0.127 (0.067)
Mumbai Year 2	9986	0.324 (0.145)	0.069 (0.081)	0.188 (0.112)
C. Grade 3				
Vadodara Year 1	4230	0.179 (0.086)	0.102 (0.085)	0.152 (0.085)
Vadodara Year 2	5819	0.418 (0.107)	0.233 (0.089)	0.354 (0.100)
D. Grade 4				
Vadodara Year 1	4196	0.190 (0.072)	0.114 (0.076)	0.166 (0.073)
Vadodara Year 2	6131	0.307 (0.078)	0.240 (0.068)	0.289 (0.074)
E. Two Year (2001-03)				
Mumbai Pretest Year 1 to Posttest Year 2	3188	0.612 (0.141)	0.185 (0.094)	0.407 (0.106)
Vadodara Pretest Year 1 to Posttest Year 2	3425	0.282 (0.094)	0.181 (0.079)	0.250 (0.088)

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Table V: Short- and Longer-Run Impacts of Programs, by Initial Pretest Score

Sample	Probability of assignment to balsakhi			Program effect in Year 2:			Persistence of program effect:		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
PAEL A: Balsakhi, 2020									
All Children	0.313	0.371 (0.073)	0.246 (0.061)	0.331 (0.070)	11950	0.053 (0.047)	0.033 (0.041)	0.040 (0.041)	9925
Bottom Third	0.446	0.469 (0.088)	0.317 (0.074)	0.425 (0.084)	4053	0.096 (0.045)	0.097 (0.038)	0.103 (0.040)	3356
Middle Third	0.341	0.374 (0.082)	0.240 (0.069)	0.339 (0.080)	3874	0.021 (0.056)	-0.024 (0.054)	0.001 (0.052)	3226
Top Third	0.162	0.229 (0.076)	0.174 (0.076)	0.216 (0.077)	4023	0.015 (0.069)	0.006 (0.062)	0.009 (0.061)	3343
PAEL B: C.AL, 2020									
All Children		0.347 (0.076)	0.013 (0.069)	0.208 (0.074)	5732	0.092 (0.045)	-0.072 (0.048)	0.008 (0.045)	4688
Bottom Third		0.425 (0.106)	0.086 (0.089)	0.278 (0.102)	1962	0.107 (0.046)	0.004 (0.047)	0.046 (0.046)	1586
Middle Third		0.316 (0.081)	0.005 (0.081)	0.183 (0.082)	1844	0.085 (0.055)	-0.105 (0.069)	-0.015 (0.058)	1511
Top Third		0.266 (0.073)	-0.033 (0.081)	0.146 (0.078)	1926	0.073 (0.072)	-0.105 (0.064)	-0.013 (0.068)	1591

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(4) Kremer, Miguel, Thornton (2007)

- Merit scholarships and schooling in rural Kenya
 - The debate over merit scholarships
- “Pros”: Incentives to exert effort, perhaps helping to deal with self-control problems, externalities to effort
- Possible “cons”: (1) Exacerbate inequality, (2) Weaken intrinsic motivation in either short or long run, (3) Gaming the system through cramming, cheating, less effort in other key dimensions

The Girls Scholarship Program (GSP)

- GSP is a randomized evaluation of a merit award for Grade 6 girls in Busia and Teso districts, Kenya
- 64 treatment schools, 63 comparison schools
- The top 15% of girls in program schools (by district) received a \$38 prize for school fees and supplies over two years, and a public awards ceremony

Two GSP research questions

- (#1) What impact do these incentives have on test scores and other measures of school performance?
 - Randomized evaluation methods

- (#2) What impact does winning the GSP award have on later schooling choices and outcomes? In particular does it make it more likely that winners stay in school?
 - Regression discontinuity methods

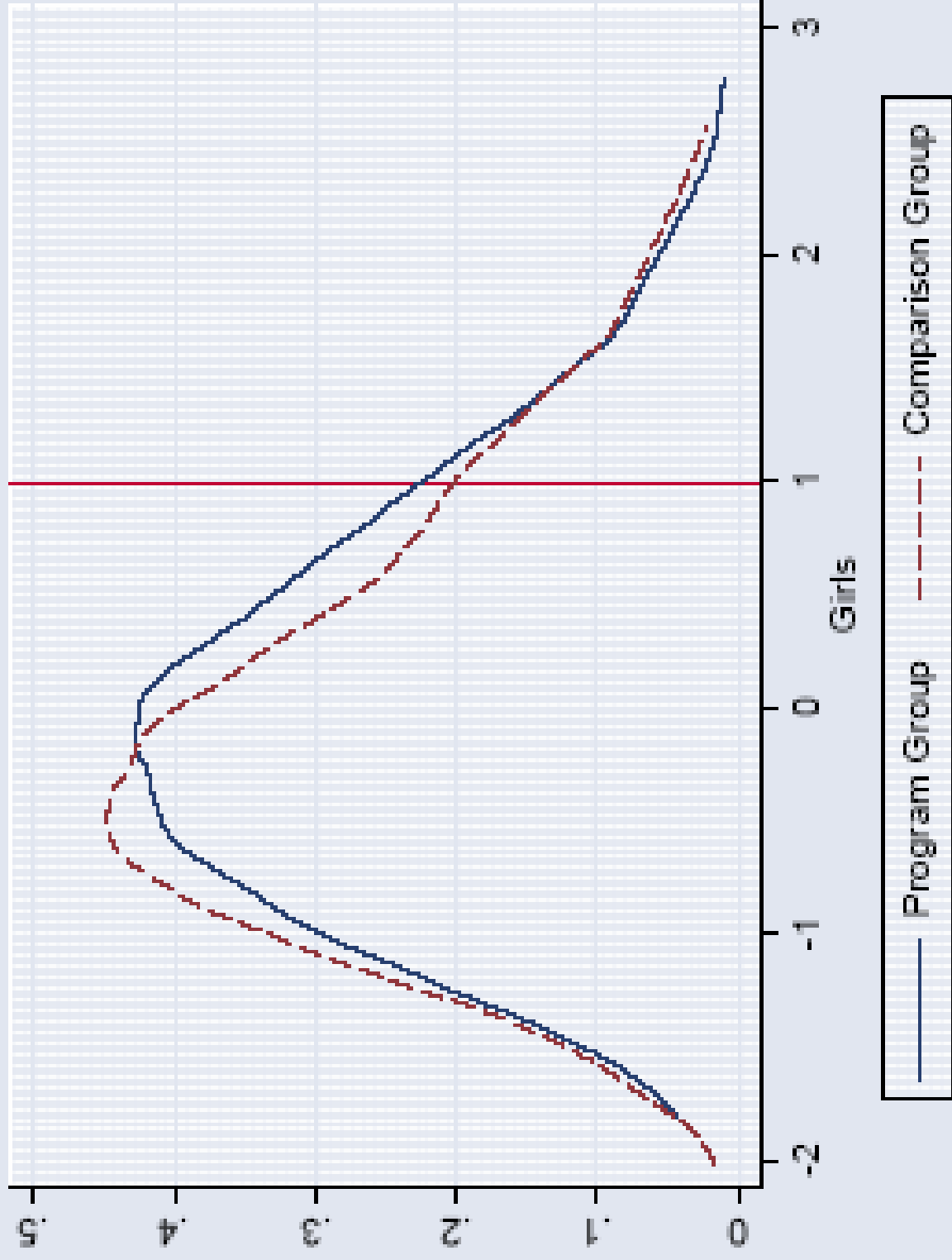
The Girls Scholarship Program (GSP)

- The randomization “worked”: treatment and comparison group schools are similar at baseline (Table 3, Figure 5)

Panel A: Busia District

	Program	Comparison	Difference (s.e.)
Age in 2001	13.5	13.4	0.0 (0.1)
Father's education (years)	5.2	5.2	0.2 (0.5)
Mother's education (years)	4.6	4.6	0.1 (0.4)
Total children in household	7.0	6.5	0.5 (0.5)
Proportion ethnic Luhya	0.49	0.47	0.03 (0.05)
Latrine ownership	0.96	0.94	0.02 (0.01)
Iron roof ownership	0.77	0.77	0.00 (0.03)
Mosquito net ownership	0.33	0.33	0.00 (0.03)
Test Score 2000–Baseline sample (cohort 1 only)	-0.05	-0.12	0.07 (0.18)
Test Score 2000–Main sample (cohort 1 only)	0.07	0.03	0.04 (0.19)

Panel (A)



Why might incentives have an impact?

Theoretical perspectives

- Extrinsic motivation (exploiting immediate gratification)
- vs. Intrinsic motivation (“love of learning”)
- Great teacher effort (altruism, recognition)
- Parent encouragement / pressure on the girls
- Community mobilization to support the program

GSP empirical impacts (2001-2002)

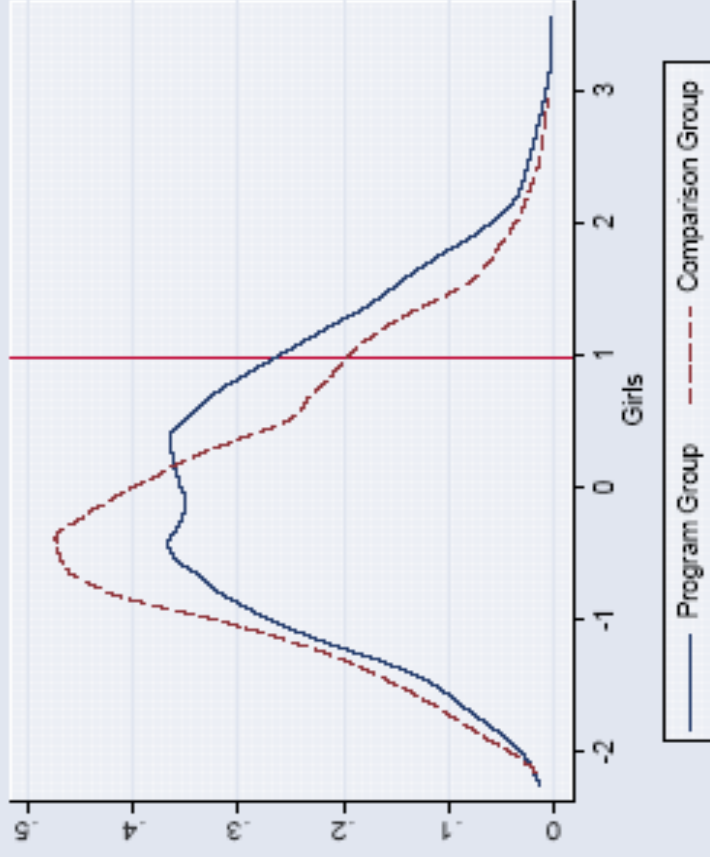
- Impacts are positive and quite large for cohort 1: 0.12-0.13 standard deviations on average (Table 4)
- There are positive effects for boys, too – even though they were not eligible for the prize: externalities
- Positive effects are concentrated in Busia district (gains of 0.2 s.d.), but are zero in Teso district – why?

Table 4: Program Impact on Test Scores
 Longitudinal Sample, Cohort 1 Girls and Boys

	Dependent variable:				
	Normalized test scores from 2001 and 2002				
	Busia and Teso districts		Busia district		Teso district
	(1)	(2)	(3)	(4)	(5)
Program school	0.12 (0.13)	0.13** (0.06)	0.12* (0.07)	0.19** (0.08)	-0.02 (0.09)
Male * Program School			0.01 (0.05)	0.01 (0.05)	0.01 (0.09)
Male			0.16*** (0.04)	0.09** (0.04)	0.28*** (0.07)
Individual test score, 2000		0.80*** (0.02)	0.79*** (0.02)	0.85*** (0.03)	0.69*** (0.02)
Sample Size	4294	4294	4294	2858	1436
R ²	0.00	0.61	0.61	0.67	0.53
Mean of dependent variable	0.13	0.13	0.13	0.13	0.12

**Figure 6: Year 1 (2001) Test Score Distribution
Cohort 1 Busia Girls (Panel A) and Busia Boys (Panel B)
(Non-parametric kernel densities)**

Panel (A)



Panel (B)

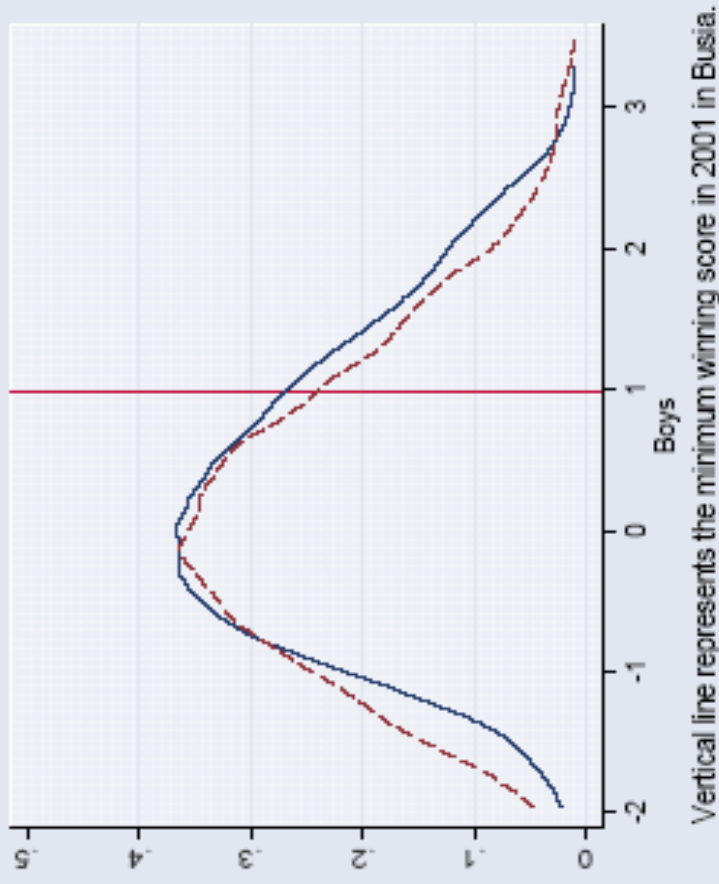
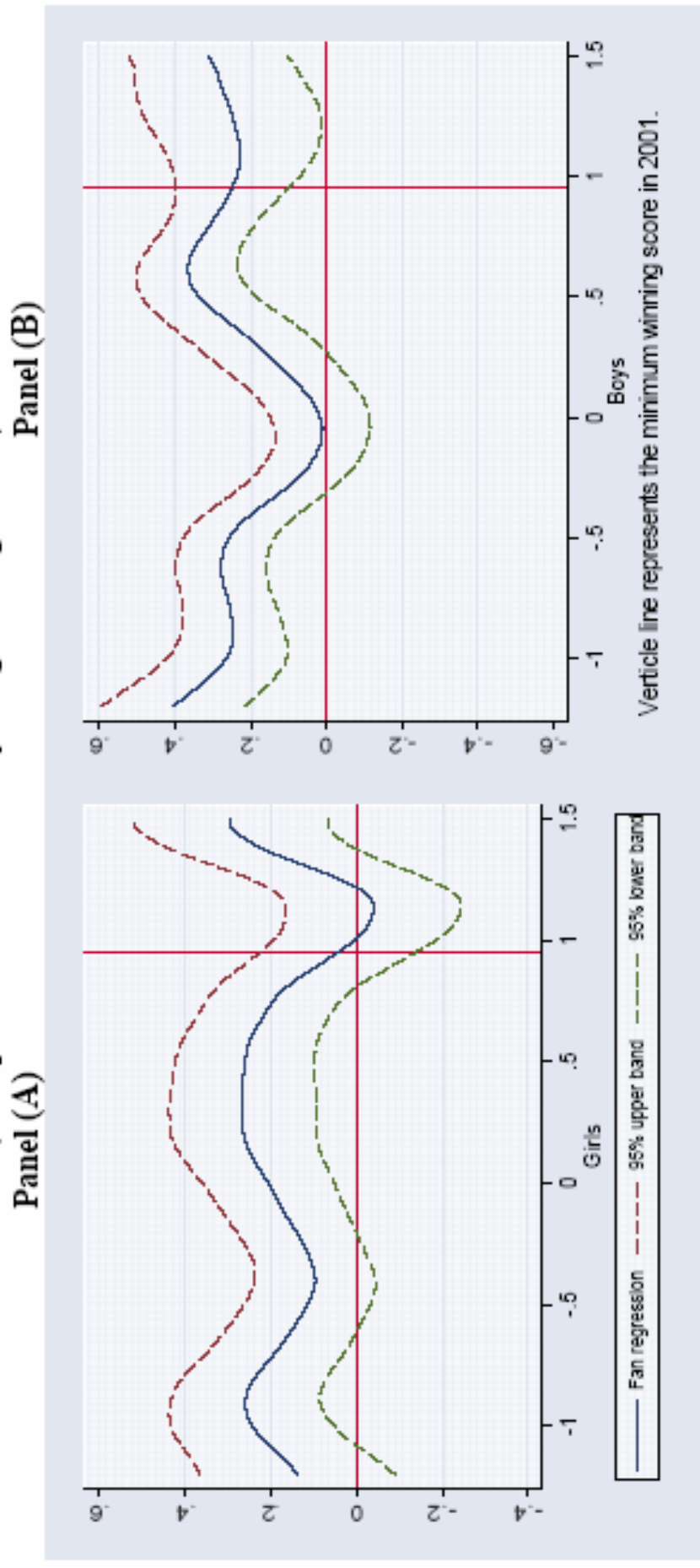


Figure 7: Year 1 (2001) Test Score Impacts by Baseline (2000) Test Score
 Difference between Program Schools and Comparison Schools
 Cohort 1 Busia Girls (Panel A) and Busia Boys (Panel B)
 (Non-parametric Fan locally weighted regression)



Difficulties in Teso district

- This NGO, and other NGOs, have long had trouble introducing new projects into Teso district
- The dominant ethnic groups are different in Busia district (Luhya) and Teso district (Teso)
- There was a tragic lightning strike incident in a Teso district primary school in April 2001 – seven students died (27 injured), and NGO project work became even more difficult afterwards. Five Teso district schools pulled out of the program

Figure 1: Map of Busia District and Teso District, Kenya, with location of Girls Scholarship Program Schools (legend below)

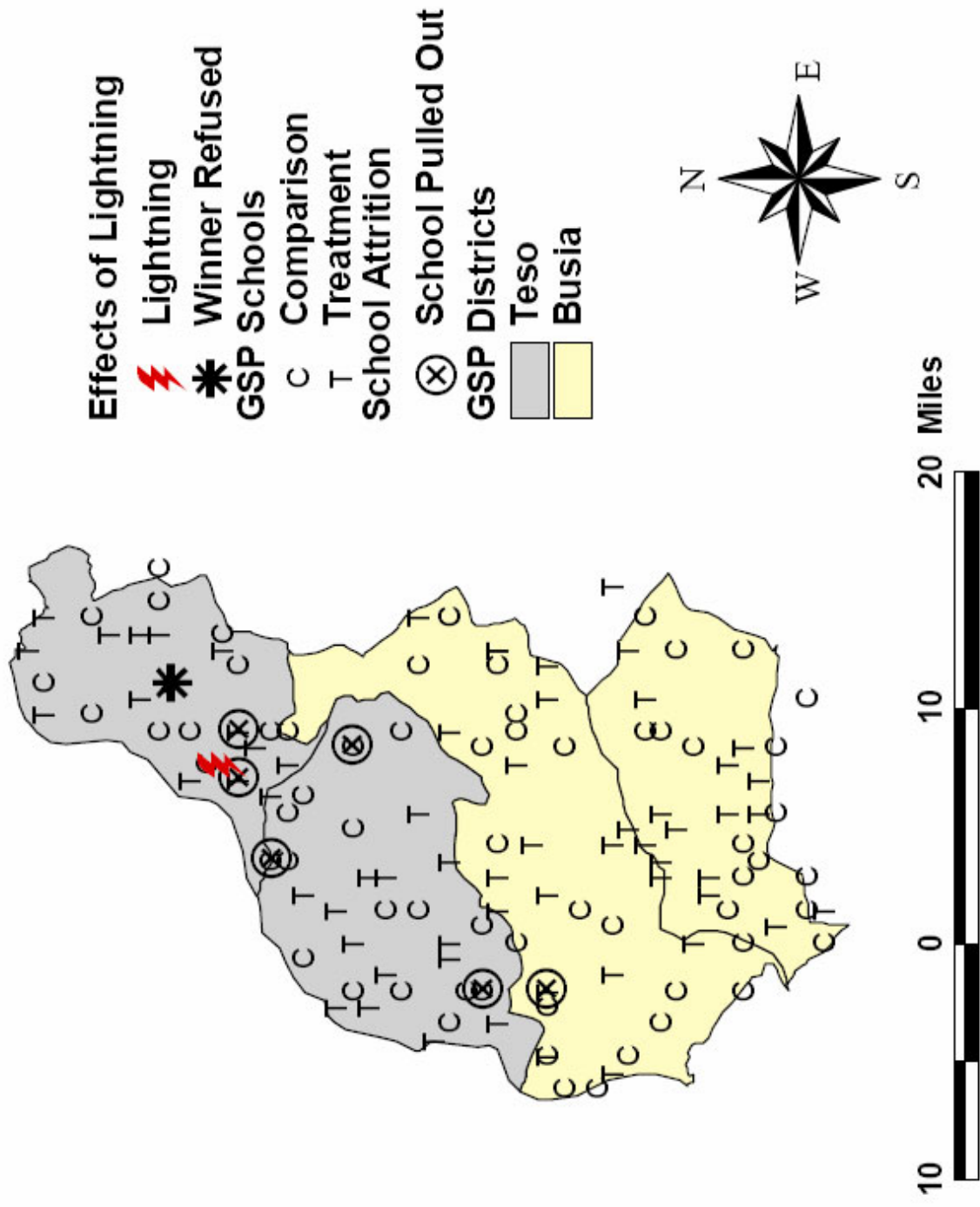


Figure 3: Proportion of Baseline Students in the 2001 Main sample by Baseline (2000) Test Score Cohort 1 Busia Girls (Panel A) and Busia Boys (Panel B)
 (Non-parametric Fan locally weighted regressions)

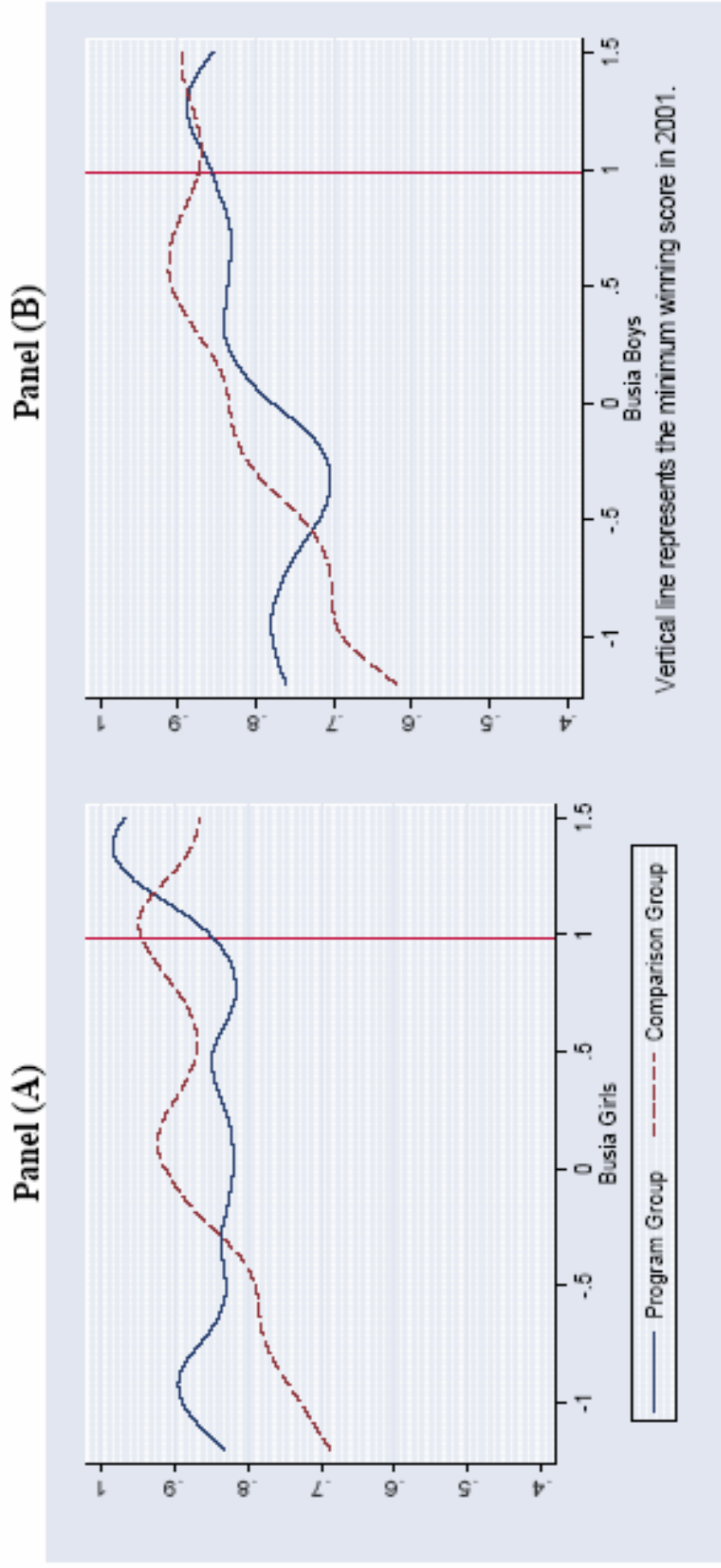


Figure 4: Proportion of Baseline Students in the 2001 Main sample by Baseline (2000) Test Score Cohort 1 Teso Girls (Panel A) and Teso Boys (Panel B)
 (Non-parametric Fan locally weighted regressions)

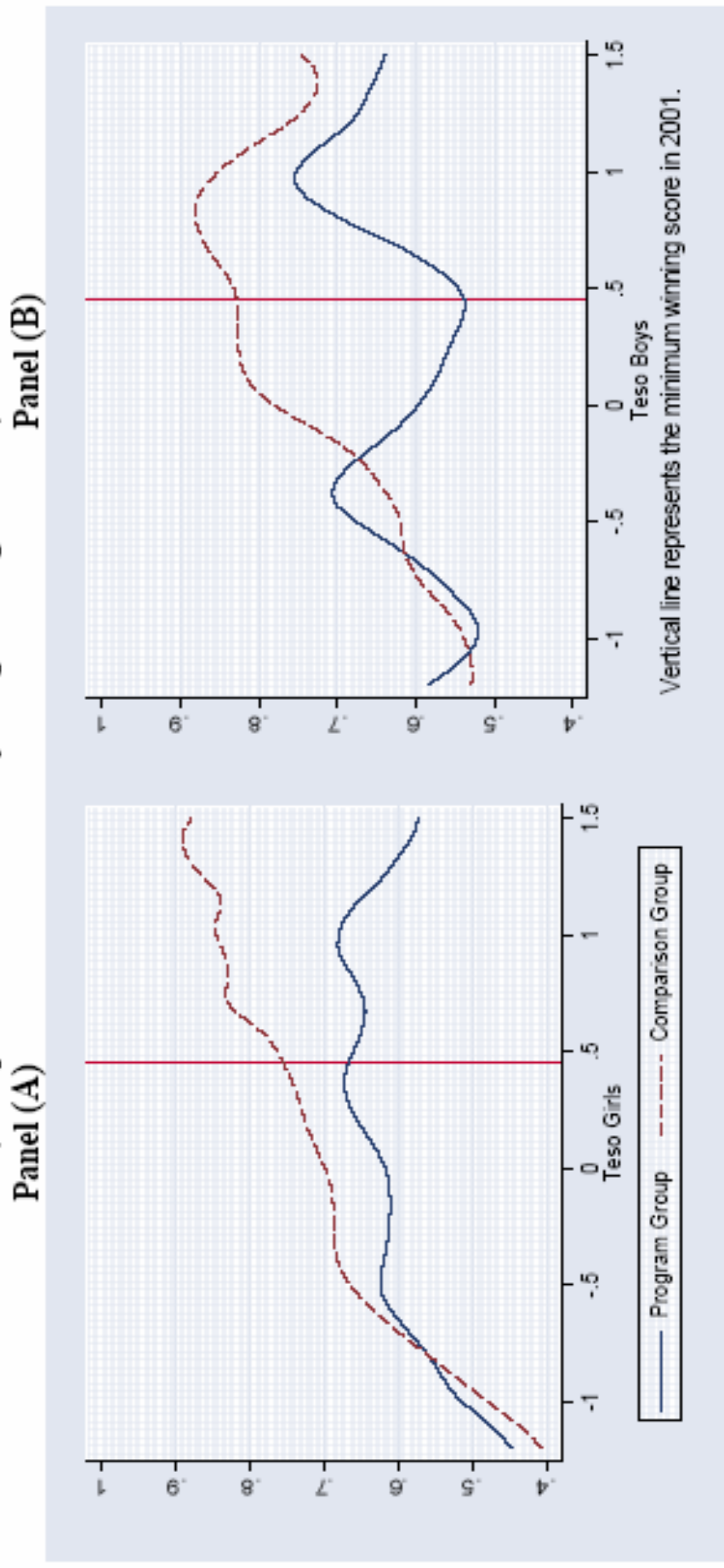


Table 5: Program Impact on Test Scores
Main sample, Cohorts 1 and 2 Girls and Boys

	Dependent variable:			
	Normalized test scores from 2001 and 2002			
	-----Girls-----	-----Boys-----		
	Busia and Teso	Busia District	Busia and Teso	Busia District
	(1)	(2)	(3)	(4)
Program year, Cohort 1 (2001)	0.18** (0.08)	0.28*** (0.10)	0.10 (0.07)	0.18** (0.09)
Program year, Cohort 2 (2002)	0.13* (0.07)	0.21** (0.10)	0.04 (0.10)	0.11 (0.13)
Post-competition year, Cohort 1 (2002)	0.12 (0.08)	0.25*** (0.09)	0.05 (0.07)	0.07 (0.09)
Mean school test score, 2000	0.75*** (0.05)	0.83*** (0.05)	0.78*** (0.06)	0.87*** (0.06)
Sample Size	4736	2917	5332	3206
R ²	0.29	0.36	0.26	0.32
Mean of dependent variable	-0.06	-0.03	0.21	0.21

Notes: Significantly different than zero at 90% (*), 95% (**), 99% (***) confidence. OLS regressions, Huber robust standard errors in parenthesis. Disturbance terms are allowed to be correlated across observations in the same school, but not across schools. Test scores were normalized such that comparison group test scores had mean zero and standard deviation one. Indicator variables are included in both specifications for Cohort 1 in 2001, Cohort 1 in 2002, and Cohort 2 in 2002 (coefficient estimates not shown). Main sample includes students who were registered in grade 6 (cohort 1) or grade 5 (cohort 2) in January 2001, in schools that did not pull out of the program, for whom we have mean school test score data in 2000, and who took the 2001 or 2002 test.

Evaluating critiques of merit scholarships

- No statistically significant changes in test score inequality in treatment schools
- Effort increased: student school participation increased by 5 percentage points in program schools (Table 7), for girls and boys in Busia district
- Teacher attendance increased 5 percentage points
- There are no significant changes in students' study habits, work at home, or attitudes toward education / stated intrinsic motivation (Table 6)

Busia and Teso Districts

-----Girls-----

Estimated Mean (s.d.)
impact (s.e.) of dep. var.

0.02 0.72
(0.01) (0.18)
0.02 0.73
(0.04) (0.44)
-0.02 0.69
(0.03) (0.46)
0.00 0.33
(0.04) (0.47)

Dependent Variables:

Panel A: Attitudes towards education

Student prefers school to other activities (index)^a

Student thinks s/he is a "good student"

Student thinks being a "good student" means "working hard"

Student thinks can be in top three in the class

Panel B: Study/Work habits

★ Student went for extra coaching in last two days

Student used a textbook at home in last week

Student did homework in last two days

Teacher asked the student a question in class in last two days

Amount of time did chores at home^b

Panel C: Educational Inputs

Number of textbooks at home

Number of new books bought in last term

0.09 3.83
(0.19) (2.15)
0.15 1.54
(0.14) (1.48)

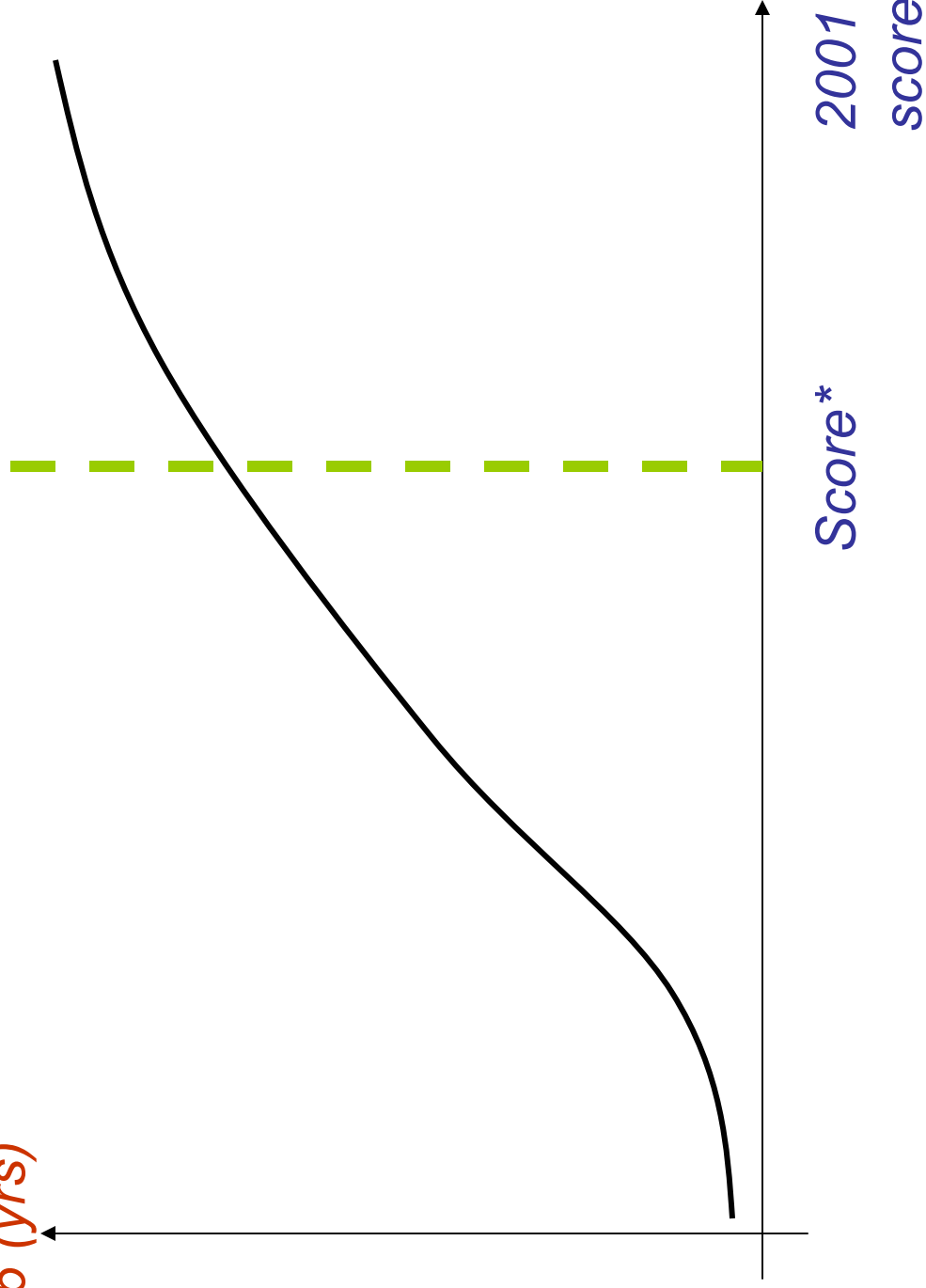
What are the policy implications?

- Positive impacts:
 - Test scores improved more than any other project we have studied in Kenya, and for relatively low cost
 - GSP could promote empowerment of women and changes in social norms about girls' education
- Possible concerns / limitations:
 - Will the impacts last? In the long-run, will GSP really destroy the “love of learning” for these kids?

What is the impact of winning the award?

- US\$38 is a lot of money in rural Kenya
 - This money went to pay for school fees, and was supposed to be used for school supplies
- Did winning the award make girls more likely to stay in school in the medium-run, through 2005-2006? (by easing credit constraints for poor households?)
- The problem for evaluation: winners are not randomly chosen. Winning is a function of one's academic performance, which we expect to have a large effect on later school attainment

Educational attainment 2005-2006 (yrs)

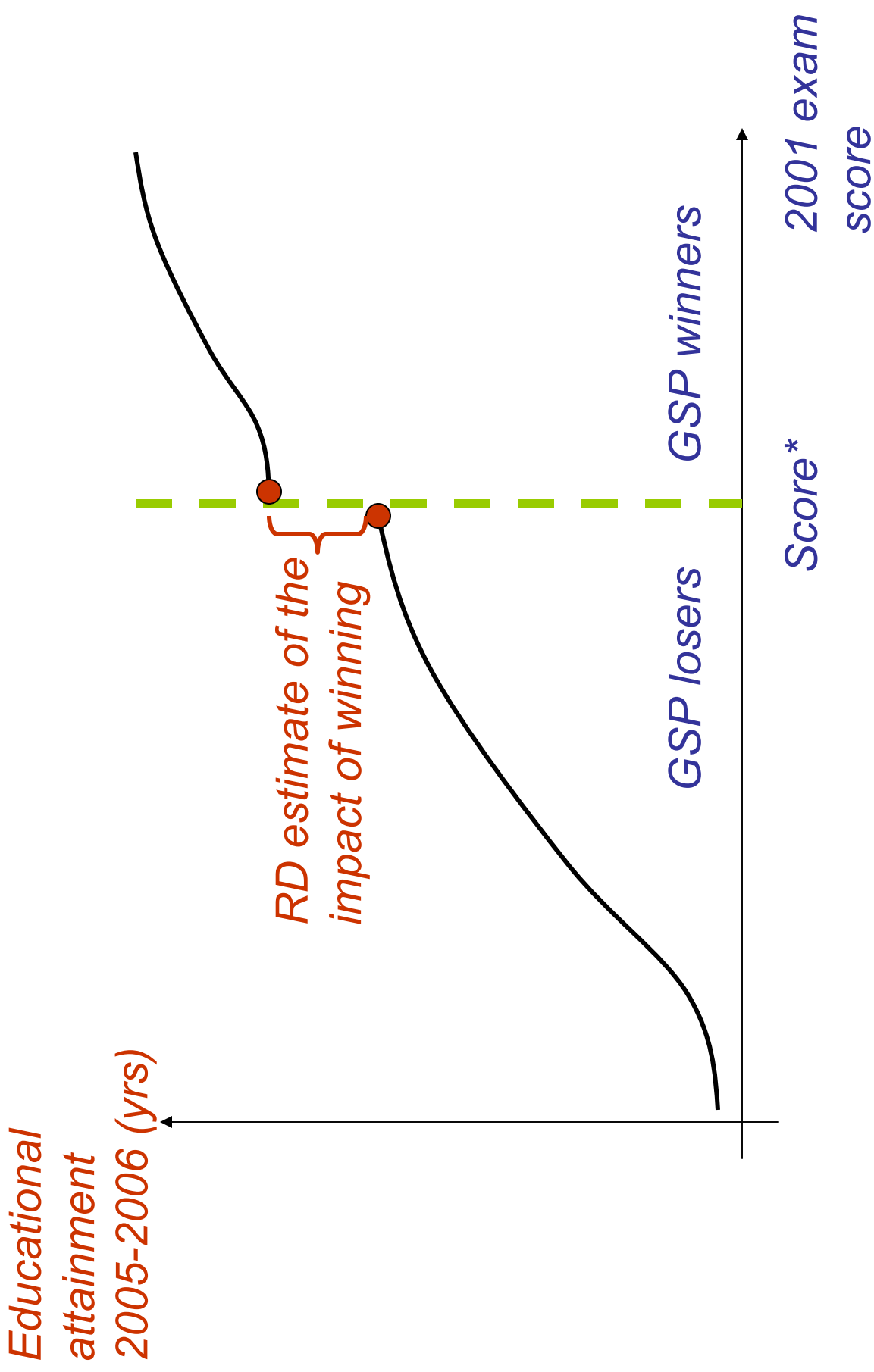


The regression discontinuity (RD) approach

- Clearly comparing winners to losers is not a very appealing strategy: the winners are much better students, so losers are not a natural comparison group
- One way to get around this is to focus on students “very close to” the winning threshold test score level
- In the limit, comparing the student who just barely won (receiving Score^*) to the student who just barely lost ($\text{Score}^* - \varepsilon$) yields a comparison group of losers almost identical to winners

The regression discontinuity (RD) approach

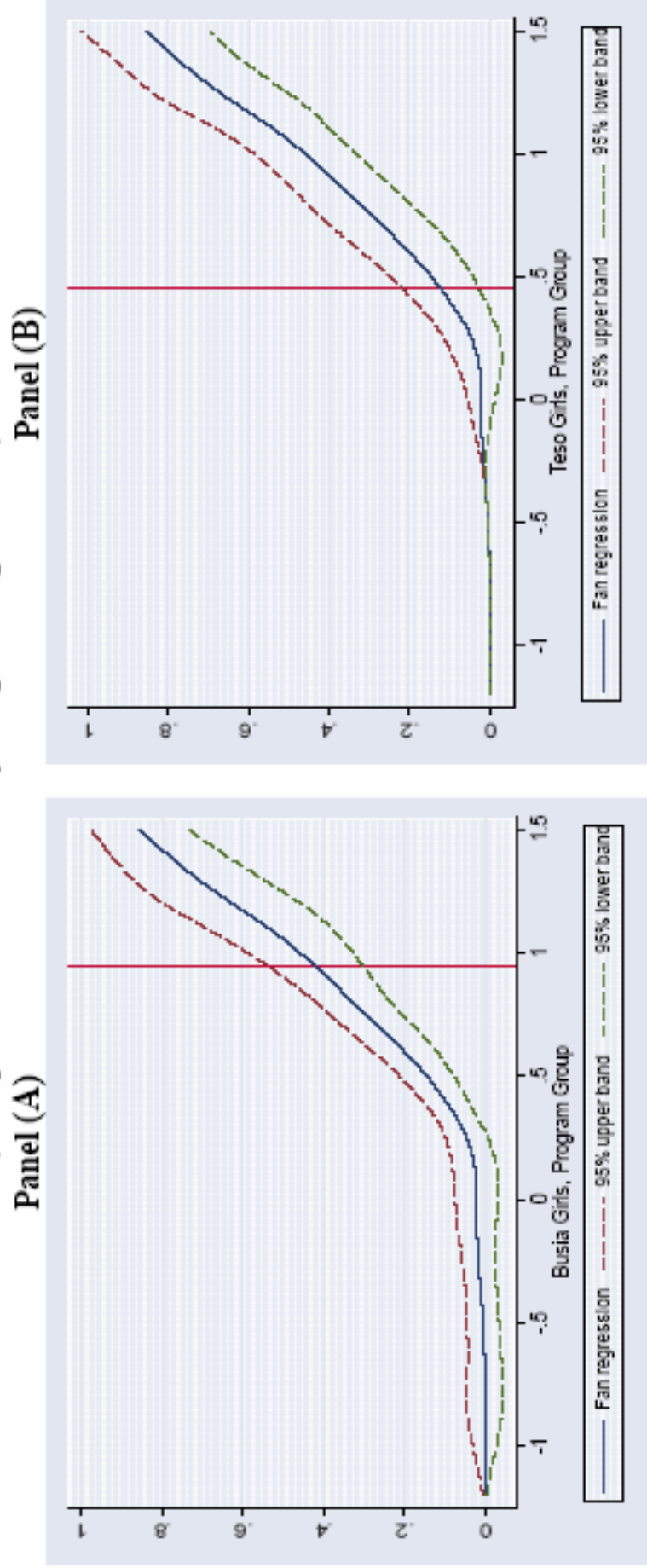
- In practice all data can be used in the analysis, but one first controls for the (smooth) polynomial test score trend and estimates any “jump” at the winning threshold test score level
- This discontinuity is the RD estimate of the impact of winning the scholarship on later school enrollment



The GSP Tracking Project (2005-2007)

- Between September 2005 – February 2007, an attempt was made to find and survey all of the GSP sample girls in Busia district. The goal: the estimate longer-term impacts of the program on their educational attainment, labor market success, marriage and fertility choices, and health
- We managed to survey 82% of the sample. The data is literally brand new (as of a few weeks ago) but some results are starting to trickle in...

Figure 1: Proportion of Baseline Students Winning the Award in 2001 by Baseline (2000) Test Score
 Cohort 1 Busia Program School Girls (Panel A) and Teso Program School Girls (Panel B)
 (Non-parametric Fan locally weighted regressions)



Whiteboard #1

Whiteboard #2

Whiteboard #3

Whiteboard #4

Whiteboard #5

