# Does BRAC Provide Highly Effective Schooling in Developing Countries?

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# Introduction

- Numerous schools providing primary education in Dhaka slums - GOV schools, NGO schools, private schools and *madrassahs*.
  - All provide traditional Bengali medium education of varying qualities.
- One such pioneer in provision of primary education - in particular non-formal primary schooling - BRAC schools.
  - BRAC claims to target out of school children, in marginalized communities, not covered by the formal schooling system.

# Introduction (contd)

- BRAC started its education program in 1985 with only 22 schools.
- BRAC now has more than 40,000 schools both in Bangladesh and internationally.
- The BRAC model has even been replicated by the Government of Bangladesh - Reaching Out of School Children (ROSC) schools.
- BRAC provides schooling in Afghanistan, Liberia, Philippines, South Sudan, Tanzania and Uganda.

# Introduction (contd)

- Given BRAC's coverage, both within Bangladesh and other developing countries, it is surprising that there very few independent evaluations of BRAC schools.
- The 3 studies that exist are done by BRAC; they find BRAC to be superior to other school-types.
- One reason for the lack of a serious evaluation of BRAC, is that there is no existing data that outside researchers can use.

# Introduction (contd)

- Since we conducted our own survey in 2015-2016 to compare JAAGO, GOV and NGO schools, we found that potentially enough BRAC students showed up for us to do relatively precise evaluations.

- We thus decided to address this lacuna in the literature, using the data we had collected; the result is that we provide the first rigorous evaluation of BRAC.

- We will need a rich data set to control for selection; we view our approach as solving an identification problem by getting better data.

- Ours is the first arms length study of BRAC schools.

# Introduction (contd)

- As mentioned in the previous slide, we also study a new innovative school-type in Dhaka's slums, called JAAGO (started in 2007), in an earlier paper.
  - JAAGO provides schooling previously available only to the elites of the country;
  - It is unique in terms of providing English medium education, strict monitoring, no corporal punishment etc.

## Research Questions

1. What type of students are being drawn to, and accepted by, each school-type: BRAC, GOV, JAAGO and Other NGOs.

2. What is the impact of school-type on test scores, before and after controlling for selection?
   (i). BRAC vs. GOV;
   (ii). BRAC vs. JAAGO;
   (iii). BRAC vs. Other NGOs.

3. We also disaggregate the sample by gender since we found it to be important in our earlier paper on JAAGO.

# Motivation and Overview of Results (cont'd)

- When we look at raw differences in achievement, BRAC students do considerably worse than the other school-types.
- But, BRAC has much more disadvantaged students than all of the other school-types.
- Hence, it is crucial that we take this selection into account when we evaluate BRAC.
- We use propensity score matching to control for selection into different school-types.

# Motivation and Overview of Results (cont'd)

- Matching of course depends entirely on the conditioning variables.
- Controlling for only family background has little effect on the estimates; but controlling for family background and IQ has a substantial effect on reducing the selection bias.
- Our use of IQ, which is quite uncommon in the literature, goes a long way towards our arguing omitted variables are not driving our results.

# Motivation and Overview of Results (cont'd)

- After controlling for this selection we find that for the pooled sample:
  - BRAC vs GOV: Students are worse off at BRAC than at GOV schools;
  - BRAC vs JAAGO: Students are worse off at BRAC than at JAAGO schools;
  - BRAC vs Other NGO: No significant difference between BRAC and other NGO schools.

# Motivation and Overview of Results (cont'd)

- When we disaggregate by gender, after we control for selection we find that:
  - BRAC vs GOV: boys do worse at BRAC than GOV schools; no significant difference between girls at the two school-types.
  - BRAC vs JAAGO: girls do worse at BRAC; no significant difference for boys at either school-type.
  - BRAC vs Other NGO: no significant difference for boys or girls at the two school-types.

# BRAC: Pioneering Non-Formal Primary Education

- Established in 1972, BRAC is now one of the largest international NGOs in the world.
- BRAC has a host of programs ranging from providing micro-credit to providing education, health care, skills development, legal and human rights services, to name a few.
- Our focus is on BRAC's Education Program - BRAC runs schools in both rural and urban areas.
- Further details can be on BRAC's website: https://www.bracinternational.nl/en/

# Characteristics Across School-types

Table 1: Comparing School-types

| Characteristics | BRAC | GOV | JAAGO | Other NGOs |
|---|---|---|---|---|
| Informal Schooling | Yes | No | No | Mixed |
| Instruction in English | No | No | Yes | No |
| Minimum teacher qualification | SSC (10 years of schooling) | Bachelor's degree* | Bachelor's degree | HSC (12 years of schooling) |
| Teachers require English Proficiency | No | No | Yes | No |
| Pre-service training | 12-15 days | 0 days | 30 days | 4 days |
| In-service training/ Refresher Courses | 30-35 days annually | 12-18 months training (C-in-ed/B-in-Ed) | need-based workshops | 6 days |
| High share of female teachers | 98-99% | 60-66% | 80% | 85% |
| Class size | 33 | 51 | 31 | 37 |
| Contact hours per day | 3.6 | 2.9 | 4.5 | 3.85 |
| School year (days per annum) | 265-270 | 228 | 265 | 247 |
| Corporal punishment | No | Yes | No | No |

Before 2013, at least SSC (completing 10 years of schooling) for female teachers and HSC (completing 12 years of schooling) for male teachers.

# BRAC's Reports: Comparing BRAC to Other School-types

Table 2: BRAC vs Other School-Types

| Study | Intervention | Methodology | Findings |
|---|---|---|---|
| Nath et al (2007) | ► Compare BRAC NFPE (non-formal schools) to GOV schools | ► Compare test-scores across school-types using means and percentages; no conditioning variables used. | ► Higher percentage of BRAC students (2.2%) completed all 27 competencies/subtests as compared to GOV students (0.9%).<br>► In terms of mean number of competencies achieved, in the absence of conditioning variables, BRAC students slightly ahead of GOV; not specified if this difference is statistically significant. |
| Nath et al. (2005) | ► Compare BRAC NFPE (non-formal schools) to BRAC formal and community schools;<br>► Community Schools - established and run by the local community with financial assistance from the government. | ► Compare test-scores across school-types using means and percentages; no conditioning variables used. | ► Out of 27 competencies, mean number of competencies achieved, in the absence of conditioning variables, is the highest for BRAC formal school students (21.2) followed by community school students (19.2) and BRAC NFPEs (18.9); not specified if mean difference is statistically significant. |
| Nath and Hossain (2017) | ► Compare BRAC NFPE schools to a National Sample from the Literacy Survey (CAMPE, 2016);<br>► National sample most likely includes a mixture of primary school-types: GOV schools, NGO schools madrassas and English medium private schools. | ► Logistic Regression. | ► After controlling for the child and family background, using logistic regression, they find that BRAC students are 2.61 times more likely to be literate than their counterparts in the national sample. |

Notes: (a)Test instrument used in Nath et al (2007, 2005) is The Achievement of Basic Competencies; it comprises of 27 competencies (subtests) on Bangla, English, Mathematics, Social studies, General Science and Religious studies; (b) CAMPE (2016) does not explicitly mention what school-types the national sample includes; we base our understanding of the national sample from earlier Education Watch reports (CAMPE 1999, 2008).

# Data Collection

- Our data is from our earlier study that used choice-based sampling to evaluate the impacts on math achievement from JAAGO, GOV and NGO schools.
- In 2015-2016 we collected our own data on approximately 600 students in each school type, in two slums of Dhaka city.
- After completing that study, we realized we could identify BRAC students among the NGO students.
- It turned out we had 239 BRAC students, 586 Government students, 576 JAAGO students, and 401 other NGO students.
- Fortunately, these sample sizes allowed us to estimate relatively precise treatment effects.

# Data Collection (cont'd)

- Given that each slum had only one JAAGO school and relatively few students went to JAAGO, with random sampling we would not have enough JAAGO students in our sample.
- Instead, we used choice-based sampling (common for studying rare events).
  - We collect the data by streets; we started with a street with a JAAGO student, then collected GOV and NGO students (inclusive of BRAC students) on the same street.
  - We have 26 clusters in our sample; we adjust the standard errors for this cluster sampling following Abadie, Athey, Imbens and Wooldridge (2017).
  - Note that the streets are very long and include side streets as well.

# School Type and Selection: Sorting?

- Investigate selection across school-types in terms of 4 key variables:
  1. Monthly Family Expenditure (deflated by equivalence scale);
  2. Father's Schooling;
  3. Mother's Schooling;
  4. K-BIT (IQ/Fluid Intelligence);
- Note that fluid intelligence, which is presumably measured by IQ tests, is defined as intelligence that is not supposed to be affected by attending school unless the schools 'teach to the test'.
- But if better school-types actually raise IQ scores more than poorer school-types, our treatment effects will be biased downwards.

# Selection: Means Across School-types

Table 3: Means by School-Type (Pooled Sample)

| | BRAC | GOV | JAAGO | Other NGOs |
|---|---|---|---|---|
| Monthly Family Expdt | 5.1830 | 6.1546 | 5.8473 | 5.4777 |
| (in BDT 1000 adjusted by equivalence scale) | (0.1565) | (0.1202) | (0.1299) | (0.1279) |
| Father's schooling | 2.3096 | 3.7025 | 3.6687 | 3.3101 |
| | (0.1745) | (0.2307) | (0.1984) | (0.3085) |
| Mother's schooling | 1.9372 | 3.2503 | 3.7995 | 2.9451 |
| | (0.1366) | (0.2268) | (0.1913) | (0.2281) |
| K-BIT (IQ) | -0.5356 | 0.0663 | 0.2646 | -0.1508 |
| | (0.0686) | (0.0672) | (0.0798) | (0.0900) |
| Observations | 239 | 586 | 576 | 401 |

Notes: (a) Standard errors in parentheses clustered at the street level; (b) For the IQ score, we use age adjusted Z-scores. In other words for student $i$ in age group $a$, we calculate, $Z_i = \dfrac{X_i - X_a}{\sigma_a}$ , where $X_a$ and $\sigma_a$ is the mean and standard deviation in age group $a$.

Boys Girls

# Selection: Mean Differences Across School-types

Table 4: Mean Differences Across School-types (Pooled Sample)

| | (1) BRAC vs GOV | (2) BRAC vs JAAGO | (3) BRAC vs Other NGOs |
|---|---|---|---|
| Monthly Family Expdt | -0.9716*** | -0.6643*** | -0.2947 |
| (in BDT 1000 adjusted by equivalence scale) | (0.2067) | (0.1929) | (0.2066) |
| Father's Schooling | -1.3929*** | -1.3591*** | -1.0004*** |
| | (0.2919) | (0.3119) | (0.2761) |
| Mother's Schooling | -1.3130*** | -1.8622*** | -1.0079*** |
| | (0.2622) | (0.2480) | (0.2209) |
| K-BIT (IQ) | -0.6019*** | -0.8002*** | -0.3848*** |
| | (0.0861) | (0.1189) | (0.0943) |
| Observations | 825 | 815 | 640 |

Notes: (a) Standard errors in parentheses clustered at the street level; (b) We report the difference in means at the 1 percent, 5 percent and 10 percent significance level denoted by *** , ** , and * respectively; (c) For KBIT (IQ score), we report age adjusted Z-scores.

Boys Girls

# Outcome Variable

- Our outcome variable: scores on the Woodcock Johnson Test of Math Achievement.
  - Widely used in the the Economics, Education and Psychology Literature.
  - Internationally developed and standardized.
- We administered these tests ourselves.

## Outcome Variable (cont'd)

- Used 3 Math oral subtests.
  - GOV, BRAC and NGO students taught in Bengali while JAAGO students taught in English;
  - Used Mathematics subtests since it is not as dependent on language skills;
  - However, administered the tests in Bengali to GOV, BRAC and NGO students; administered the same tests to JAAGO students in "Banglish" (i.e. kept technical terms in English).

# Methodology: Dealing with Selection

- We cannot use IV to solve the problem that school-type is endogenous;
  - IV yields inconsistent estimates in the presence of choice-based sampling [Solon, Haider and Wooldridge (2015)].
- Solution: We use propensity score matching to compare school-type 1 to school-type 2.
- With choice-based sampling, standard propensity score matching does not yield consistent estimates.
- To consistently estimate treatment effects, match on log odds ratio (LOR) of the estimated propensity score [Heckman and Todd (2009) and Hahn, Ham, Khan and Ridder (2020)].

# Propensity Score Matching: Estimating ATT

- For expository purposes, in what follows, we let the BRAC individuals be the treatment students and GOV individuals be the comparison students.
- Consider Average Treatment on the Treated (ATT)
  - ATT captures the effects, on achievement, of going to BRAC as opposed to GOV schools for BRAC students.

# Local Linear Regression Matching

- The Average Treatment Effect on the Treated (ATT) is:

$$\frac{1}{N_1}\sum_{D_i=1}(Y_{1i}-\widehat{Y_{0i}})=\frac{1}{N_1}\sum_{D_i=1}(Y_{1i})-\frac{1}{N_1}\sum_{D_i=1}(\widehat{Y_{0i}})$$

where

- $Y_{1i}$ : observed test score of child $i$ going to BRAC;
- $\widehat{Y_{0i}}$ : predicted test score of BRAC child $i$ if s/he had gone to GOV; we use local linear regression matching methods to construct this counterfactual.

LLM

# Trimming: Common Support

- We trim the data to achieve common support.
  - Continuing with the example of *BRAC vs. GOV* students, we do not want to estimate the ATT for *BRAC vs. GOV* from data points where there are very few or no GOV students around each BRAC child in terms of estimated log odds ratio.

# Estimating ATT (Pooled Sample)

Table 5: **Estimating ATT using Matching to Control for Selection (Data Driven Bandwidth using Epanechnikov Kernel)**

| | Dependent Variable - Achievement Test Z-Score | | |
|---|---|---|---|
| | (1) **Mean Difference (no controls)** | (2) **Only Family Background (no IQ)** | (3) **Family Background & K-BIT** |
| **BRAC vs GOV** | -0.5465*** | -0.6118*** | -0.2723** |
| | (0.1211) | (0.1220) | (0.1121) |
| *p-value* | | 0.0000 | 0.0151 |
| *bandwidth* | | 0.53 | 0.55 |
| **BRAC vs JAAGO** | -0.7311*** | -0.8049*** | -0.4483*** |
| | (0.1292) | (0.1264) | (0.1156) |
| *p-value* | | 0.0000 | 0.0001 |
| *bandwidth* | | 0.61 | 0.49 |
| **BRAC vs Other NGOs** | -0.3175*** | -0.2481** | -0.0365 |
| | (0.1107) | (0.1120) | (0.1108) |
| *p-value* | | 0.0267 | 0.7419 |
| *bandwidth* | | 0.49 | 0.32 |

Notes: (a) Bootstrapped standard errors in parentheses clustered at the street level; (b) We report Treatment Effects at the 1 percent, 5 percent and 10 percent significance level denoted by *** , ** , and * respectively; (c) Family background matching covariates consist of gender, child's age, family size, father absence dummy, father's schooling and mother's schooling; (d) For sample size, refer to Tables 4.

# Estimating ATT (Disaggregated by Gender): BRAC vs GOV

Table 6: **Estimating ATT using Matching to Control for Selection (Data Driven Bandwidth using Epanechnikov Kernel)**

| | Dependent Variable - Achievement Test Z-Score | | |
|---|---|---|---|
| | (1) **Mean Difference (no controls)** | (2) **Only Family Background (no IQ)** | (3) **Family Background & K-BIT** |
| **BRAC vs GOV (girls)** | -0.4026$^{***}$<br>(0.1242) | 0.2666$^{*}$<br>(0.1520) | -0.0777<br>(0.1924) |
| *p-value* | | 0.0793 | 0.6864 |
| *bandwidth* | | 0.16 | 0.27 |
| **BRAC vs GOV (boys)** | -0.7069$^{***}$<br>(0.1488) | -0.8244$^{***}$<br>(0.1790) | -0.5464$^{**}$<br>(0.2787) |
| *p-value* | | 0.0000 | 0.0499 |
| *bandwidth* | | 0.18 | 0.3 |

Notes: (a) Bootstrapped standard errors in parentheses clustered at the street level; (b) We report Treatment Effects at the 1 percent, 5 percent and 10 percent significance level denoted by $^{***}$ , $^{**}$ , and $^{*}$ respectively; (c) Family background matching covariates consist of child's age, family size, father absence dummy, father's schooling and mother's schooling; (d) For sample size, refer to Tables 11 and 12.

# Estimating ATT (Disaggregated by Gender): BRAC vs JAAGO

Table 7: **Estimating ATT using Matching to Control for Selection (Data Driven Bandwidth using Epanechnikov Kernel)**

| | Dependent Variable - Achievement Test Z-Score | | |
|---|---|---|---|
| | (1) **Mean Difference (no controls)** | (2) **Only Family Background (no IQ)** | (3) **Family Background & K-BIT** |
| **BRAC vs JAAGO (girls)** | -0.6509*** | -0.6669*** | -0.4111** |
| | (0.1210) | (0.1541) | (0.1652) |
| *p-value* | | 0.0000 | 0.0128 |
| *bandwidth* | | 0.11 | 0.22 |
| **BRAC vs JAAGO (boys)** | -0.8279*** | -0.8664*** | -0.2041 |
| | (0.1678) | (0.1741) | (0.2187) |
| *p-value* | | 0.0000 | 0.3508 |
| *bandwidth* | | 0.25 | 0.31 |

Notes: (a) Bootstrapped standard errors in parentheses clustered at the street level; (b) We report Treatment Effects at the 1 percent, 5 percent and 10 percent significance level denoted by *** , ** , and * respectively; (c) Family background matching covariates consist of child's age, family size, father absence dummy, father's schooling and mother's schooling; (d) For sample size, refer to Tables 11 and 12.

# Estimating ATT (Disaggregated by Gender): BRAC vs Other NGOs

Table 8: **Estimating ATT using Matching to Control for Selection (Data Driven Bandwidth using Epanechnikov Kernel)**

| | Dependent Variable - Achievement Test Z-Score | | |
|---|---|---|---|
| | (1) **Mean Difference (no controls)** | (2) **Only Family Background (no IQ)** | (3) **Family Background & K-BIT** |
| **BRAC vs Other NGOs (girls)** | -0.2430*** | -0.1359 | 0.0520 |
| | (0.1144) | (0.1362) | (0.1554) |
| *p-value* | | 0.3183 | 0.7381 |
| *bandwidth* | | 0.09 | 0.17 |
| **BRAC vs Other NGOs (boys)** | -0.4151*** | -0.3831* | -0.1896 |
| | (0.1605) | (0.2114) | (0.1973) |
| *p-value* | | 0.0700 | 0.3366 |
| *bandwidth* | | 0.17 | 0.25 |

Notes: (a) Bootstrapped standard errors in parentheses clustered at the street level; (b) We report Treatment Effects at the 1 percent, 5 percent and 10 percent significance level denoted by *** , ** , and * respectively; (c) Family background matching covariates consist of child's age, family size, father absence dummy, father's schooling and mother's schooling; (d) For sample size, refer to Tables 11 and 12.

# Balancing Tests for Matching Covariates

- We pass the balancing test for all variables when we use the full model to estimate the log odds ratio;
- On the other hand, if we use only family background variables (excluding IQ) to estimate the log odds ratio, we fail the balancing test for variables like K-BIT.

# Key Findings

- BRAC attracts/targets ‘weaker’ students:
  - Students with higher IQ and relatively better educated parents sorted into JAAGO, GOV and other NGO schools.
  - ‘Weaker’ students sorted into BRAC schools.
- Family Background alone does not play much of a role in controlling for selection.
- Fluid Intelligence plays a crucial part in controlling for selection.
  - Including fluid intelligence, as measured by K-BIT, which most developing country studies fail to account for, substantially reduces bias.

# Key Findings (cont'd)

- After controlling for selection,
  - Students perform worse at BRAC as compared to their counterparts at GOV and JAAGO schools;
  - No difference between students at BRAC and other NGO schools in terms of their math achievement.
- When we separate by gender,
  - Boys perform worse at BRAC than at GOV; no significant difference between boys at BRAC vs JAAGO and BRAC vs NGO.
  - Girls perform worse at BRAC than at JAAGO; no significant difference between girls at BRAC vs GOV and BRAC vs NGO.

# Thank You

# What if school-type affects IQ? (cont'd)

- Suppose schooling does affect IQ, and better school types raise IQ more.
  - Then it is straight-forward to show our J vs B and G vs B effects are downward biased.
  - Intuition: IQ is taking part of the credit for school type.
  - This would mean that the school-type effect is underestimated and the selection effect is overestimated.
  - A similar argument holds for log odds based matching.

# What if school-type affects IQ?

- Our IQ measures are intended to measure:
  - *fluid* intelligence (i.e. intelligence not affected by schooling) and NOT *crytallized* intelligence, as shown in numerous studies [e.g. Blair and Razza (2007); Fitzpatrick et al. (2014); Swanson (2008, 2011)] .
- It is possible to improve certain IQ test scores (e.g. Raven's) by teaching to the test; however, such training is not common in the average slum schools of Bangladesh.
- K-BIT scores tend to increase by age; to account for this, we normalize each score by age.

## What if school-type affects IQ? (cont'd)

- Let S = index of schooling quality and $\frac{\partial IQ}{\partial S} > 0$

$$\frac{dAch}{dS} = \frac{\partial Ach}{\partial S}|_{dIQ=0} + \frac{\partial Ach}{\partial IQ}\frac{\partial IQ}{\partial S}$$

- We estimate:

$$\frac{\partial Ach}{\partial S}|_{dIQ=0} = \frac{dAch}{dS} - \frac{\partial Ach}{\partial IQ}\frac{\partial IQ}{\partial S}$$

or,

$$\frac{\partial Ach}{\partial S}|_{dIQ=0} < \frac{dAch}{dS}$$

since $\frac{\partial Ach}{\partial IQ}\frac{\partial IQ}{\partial S} > 0$

# Selection: Means Across School-types (Boys)

Table 9: Means by School-Type (Boys)

| | BRAC | GOV | JAAGO | Other NGOs |
|---|---|---|---|---|
| Monthly Family Expdt | 5.3479 | 6.2623 | 5.8478 | 5.4961 |
| (in BDT 1000 adjusted by equivalence scale) | (0.2256) | (0.1460) | (0.1873) | (0.1596) |
| Father's schooling | 2.7273 | 3.8987 | 4.0212 | 3.3333 |
| | (0.3315) | (0.2598) | (0.2672) | (0.4036) |
| Mother's schooling | 2.1712 | 3.2368 | 3.7327 | 2.9211 |
| | (0.2489) | (0.2213) | (0.2504) | (0.2690) |
| K-BIT (IQ) | -0.5550 | 0.0439 | 0.3582 | -0.1480 |
| | (0.1125) | (0.0520) | (0.0792) | (0.1177) |
| Observations | 110 | 278 | 260 | 171 |

Notes: (a) Standard errors in parentheses clustered at the street level; ((b) For the IQ score, we use age adjusted Z-scores. In other words for student $i$ in age group $a$, we calculate, $Z_i = \dfrac{X_i - X_a}{\sigma_a}$, where $X_a$ and $\sigma_a$ is the mean and standard deviation in age group $a$.

Means (Pooled)

# Selection: Means Across School-types (Girls)

Table 10: Means by School-Type (Girls)

| | BRAC | GOV | JAAGO | Other NGOs |
|---|---|---|---|---|
| Monthly Family Expdt | 5.0424 | 6.0575 | 5.8470 | 5.4639 |
| (in BDT 1000 adjusted by equivalence scale) | (0.1519) | (0.1281) | (0.1277) | (0.1230) |
| Father's schooling | 1.9535 | 3.5254 | 3.3787 | 3.2928 |
| | (0.1800) | (0.2501) | (0.2050) | (0.2994) |
| Mother's schooling | 1.7377 | 3.2624 | 3.8544 | 2.9630 |
| | (0.1837) | (0.2877) | (0.1913) | (0.2428) |
| K-BIT (IQ) | -0.5190 | 0.0865 | 0.1876 | -0.1529 |
| | (0.0570) | (0.0936) | (0.1016) | (0.0868) |
| Observations | 129 | 308 | 316 | 230 |

Notes: (a) Standard errors in parentheses clustered at the street level; (b) For the IQ score, we use age adjusted Z-scores. In other words for student $i$ in age group $a$, we calculate, $Z_i = \dfrac{X_i - X_a}{\sigma_a}$, where $X_a$ and $\sigma_a$ is the mean and standard deviation in age group $a$.

Means (Pooled)

# Selection: Mean Differences Across School-types (Boys)

Table 11: Mean Differences Across School-types (Boys)

| | (1)<br>BRAC<br>vs<br>GOV | (2)<br>BRAC<br>vs<br>JAAGO | (3)<br>BRAC<br>vs<br>Other NGOs |
|---|---|---|---|
| Monthly Family Expdt | -0.9144*** | -0.4999 | -0.1483 |
| (in BDT 1000 adjusted by equivalence scale) | (0.2829) | (0.3160) | (0.2910) |
| Father's Schooling | -1.1714** | -1.2939** | -0.6061 |
| | (0.4336) | (0.5207) | (0.4363) |
| Mother's Schooling | -1.0656*** | -1.5615*** | -0.7498** |
| | (0.3100) | (0.3409) | (0.2932) |
| K-BIT (IQ) | -0.5989*** | -0.9132*** | -0.4070*** |
| | (0.1185) | (0.1628) | (0.1394) |
| Observations | 388 | 270 | 281 |

Notes: (a) Standard errors in parentheses clustered at the street level; (b) We report the difference in means at the 1 percent, 5 percent and 10 percent significance level denoted by *** , ** , and * respectively; (c) For KBIT (IQ score), we report age adjusted Z-scores.

Mean Differences (Pooled)

# Selection: Mean Differences Across School-types (Girls)

Table 12: Mean Differences Across School-types (Girls)

| | (1) BRAC vs GOV | (2) BRAC vs JAAGO | (3) BRAC vs Other NGOs |
|---|---|---|---|
| Monthly Family Expdt | -1.0150*** | -0.8045*** | -0.4215** |
| (in BDT 1000 adjusted by equivalence scale) | (0.2082) | (0.1426) | (0.1976) |
| Father's Schooling | -1.5719*** | -1.4252*** | -1.3393*** |
| | (0.3102) | (0.2984) | (0.2964) |
| Mother's Schooling | -1.5247*** | -2.1167*** | -1.2253*** |
| | (0.3569) | (0.3095) | (0.3216) |
| K-BIT (IQ) | -0.6056*** | -0.7066*** | -0.3661*** |
| | (0.1069) | (0.1259) | (0.0892) |
| Observations | 437 | 445 | 359 |

Notes: (a) Standard errors in parentheses clustered at the street level; (b) We report the difference in means at the 1 percent, 5 percent and 10 percent significance level denoted by ***, ** , and * respectively; (c) For KBIT (IQ score), we report age adjusted Z-scores.

Mean Differences (Pooled)

# Local Linear Regression Matching

- When estimating the ATT, local linear regression matching methods construct the counterfactual by solving the following minimization problem for each BRAC student $i$ and setting the counterfactual to $\widehat{\beta}_{0i} = \widehat{Y_{0i}}$:

$$\min_{\beta_0,\beta_1} \sum_{j=1}^{N_2} \left\{ Y_j^0 - \beta_{0i} - \beta_{1i}\left[\hat{l}(x_j) - l_i\right] \right\}^2 K\left(\frac{\hat{l}(x_j) - l_i}{h}\right)$$

where

- $K(.)$ is the kernel weighting function;
- $\hat{l}$ is the log odds ratio, i.e., $\hat{l} = log\left[\frac{\hat{p}}{1-\hat{p}}\right]$;
- $h$ is the bandwidth;
- $j$ refers to GOV students whose total number is $N_2$.

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# Balancing Tests

Table 13: **Balancing Tests at the 5% level for Matching Estimators with Different Trimming Methods, Data Driven Bandwidth and the Epanechnikov Kernel**

| | Matching using 1:5 Trim and Data Driven Bandwidth | |
|---|---|---|
| | (1)<br>LOR estimated using correctly specified model (including IQ) | (2)<br>LOR estimated using misspecified model (excluding IQ) |
| **BRAC vs GOV** | 0 | 1 |
| **BRAC vs JAAGO** | 0 | 1 |
| **BRAC vs Other NGOs** | 0 | 1 |

Notes: (a) Log Odds Ratio (LOR) estimated using the misspecified model uses 5 covariates. This includes child's age, gender, family size, father absence dummy, father's schooling and mother's schooling; (b) Log Odds Ratio (LOR) estimated using correctly specified model uses all 8 matching covariates. This includes the standard set of 6 family background variables mentioned in (a) as well as IQ measures, i.e., Raven's and K-BIT Z-scores.