Selection, Gender and the Impact of Schooling Type in the Dhaka Slums: Much Better Data Matters!

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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.
  - GOV and NGO schools dominate schooling provision in slums.
  - NGO schools treated as substitutes of government schools.
  - No evidence how GOV and NGO schools compare in terms of learning outcomes in urban Bangladesh.

Introduction (contd)

- In 2007, a new school-type called JAAGO started operating in two slums of Dhaka.
  - JAAGO is unique in terms of providing English medium education, strict monitoring, no corporal punishment etc;
  - This type of schooling previously available only to the elites of the country.
- There is no existing data we could use to evaluate JAAGO, so we collected our own data.

Research Questions

1. What type of students are being drawn to, and accepted by, each school-type?
   - Is there selection across school-types for boys and girls?

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

3. Within each school-type, how do boys and girls perform after controlling for selection?

Presentation Outline

1. Motivation & Overview of Results
2. School-type Characteristics & Data Collection
3. Evidence of Selection
4. Estimation Methods
5. Results: Across School-Types Comparisons
6. Results: Within School-Types Comparisons
7. Conclusion

Motivation and Overview of Results

In the context of Bangladesh:

1. No evidence about impact of school-type on student achievement and gender differential for urban Bangladesh.

2. High enrolment at primary level, but poor learning outcomes [World Bank, 2013].

3. Gender parity in primary school enrolment, but not in achievement [World Bank (2013), ADB Country Gender Assessment Bangladesh (2010)].

In a wider context:

4. Similar low student achievement and wide gender gap in Pakistan [Das, Pandey and Zajonc (2012), The Economist (Jan 4, 2018)].

Motivation and Overview of Results (contd)

- Given the poor learning outcomes and gender gap in both countries (combined population of 380 million), it is important to:
  - compare the two dominant school-types - GOV and NGO schools;
  - consider an alternative schooling model, JAAGO.

Motivation and Overview of Results (cont'd)

- Our results indicate strong evidence of gender heterogeneity across school-types.
  - GOV vs. NGO: Boys are better off at GOV schools, but girls perform equally at both school-types.
  - JAAGO vs. GOV: Girls are better off at JAAGO, but boys perform equally at both school-types.
  - JAAGO vs. NGO: Both genders better off at JAAGO.

Motivation and Overview of Results (cont'd)

- Our work can explain the gender achievement gap in Bangladesh.
- We also find within school type gender differences for GOV schools.
- After controlling for the X's:
  - we do not see any difference in achievement between comparable boys and girls at JAAGO and NGO schools;
  - However, we see boys doing significantly better than comparable girls at GOV schools.
- Since the vast majority of students go to either GOV or NGO schools, the boys' aggregate achievement has to be higher.

Motivation and Overview of Results (cont'd)

- But introducing JAAGO should help to equalize gender outcomes.
- At JAAGO, girls do better than if they attended government or NGO schools, and girls do equally well as boys at JAAGO.
- Thus, JAAGO may help attain gender parity in terms of achievement, and reduce aggregate gender differences in achievement.

Methodological Contributions

- When collecting our data we had to be conscious of the fact that in Dhaka only a miniscule fraction of students go to JAAGO schools.
- Hence we needed to use Choice Based Sampling.
  - Since IV does not produce consistent results for a Choice Based Sample, it did not make sense to worry about finding/collecting data on potential instruments such as distance to each school type.
- Instead we turned to matching to solve the selection problem of which students go to which schools.
  - Propensity Score Matching does not provide consistent results with a Choice Based Sample, but matching on the log odds ratio for the propensity score does yield consistent estimates here.

Methodological Contributions (cont'd)

- Hence we put our emphasis on collecting good conditioning variables for who goes to which school.
  - Since we did not want to assume that family background variables would allow us to achieve the Conditional Independence Assumption (e.g Foster and Rosenzweig) we collected two IQ measures, Ravens and K-Bit, for each student by administering the tests ourselves.
  - We found that conditioning on these measures, particularly K-BIT really affected our school type treatment effects. We view our approach as solving an identification problem by getting more and better data.
- We collected data on approximately the same number of students by school-type, which let us estimate similar treatment effects (ATEs) across school-types.

The New Kid on the Block: JAAGO

- JAAGO Foundation is a Civil Society Organization (CSO) that started operations in 2007 with one physical school in the Rayerbazar slum of Dhaka city.
- As of 2019, JAAGO Foundation has 3 projects: (i) the Education Program; (ii) the Youth Development Program; and (iii) the Rohingya Refugee Project.
- We focus on their Education Program in Bangladesh which consists of 3 offline (physical) schools and 9 online schools.

The New Kid on the Block: JAAGO (cont'd)

- Of the 3 off-line schools, 2 are located in Dhaka, while one is located in Chittagong, a southern city of Bangladesh (distinct from Dhaka in terms of distance, economic structure, income scale etc).
- JAAGO also has 9 online schools located in different parts of Bangladesh (outside Dhaka).
  - Each of these location consist of a brick and mortar structure where students come for their regular classes and learn their lessons from the 'teacher in the TV'.
  - We do not consider these online schools since they are quite different from the physical schools.

The New Kid on the Block: JAAGO (cont'd)

- JAAGO education programs are funded through both individual sponsors (located in Bangladesh and abroad) and corporate sponsors.
  - Under the child sponsorships program, individuals are matched with a JAAGO student(s);
  - Each sponsor parent provides a monthly contribution of BDT 2000 (USD 23.6) per child;
  - Not all JAAGO students have sponsor parents;
  - To make up the difference, JAAGO relies on corporate partnerships with different organization which provide either monetary or in-kind donations.

- Further details can be found on the JAAGO website: https://jaago.com.bd

Characteristics Across the 3 School-types

Characteristics	JAAGO	GOV	NGO
Instruction in English	✓	×	×
Minimum teacher qualification - Bachelors Degree	✓	×	×
Teachers require strong command over English	✓	×	×
High level in-service training	×	✓	×
High share of female teachers	✓	×	✓
High teacher absenteeism (low teacher effort)	×	✓	NA
High headmaster absenteeism (low monitoring)	×	✓	NA
High teacher salary	×	✓	×
Small class size	✓	×	✓
Longer school days	✓	×	×
Longer school year	✓	×	×
Corporal punishment	×	✓	×

Data Collection

- Between 2015-2016, collected our own stratified (by school type) data on 1936 slum children (aged 4 - 14) attending the 3 types of schools.
  - JAAGO schools - 607 children;
  - Government schools - 618 children;
  - NGO schools - 711 children.
- Since the Raven's Coloured Progressive Matrices (one of the IQ measures used in our analysis) is designed for children aged between 5 years and 11 years 11 months, for most of our analysis we focus on the under-12 sample of 1803 students (aged 5 to 11:11):
  - JAAGO schools - 576 children;
  - Government schools - 586 children;
  - NGO schools - 641 children.

Data Collection (cont'd)

- Took many steps, including 100% audio auditing, to insure data quality.
- Used Choice Based Sampling to ensure sufficient number of JAAGO students show up in the sample (common for sampling of rare events).
  - We collect the data by streets. We start with a street with a JAAGO student, then collect other 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).

Distributions of Schools by School Type in Our Sample

Table 1: **Summary Statistics of Schools by School Type**

	(1) No. of schools	(2) Mean (no. of students)	(3) Std. Dev	(4) Total (no. of students)
JAAGO	2	303.50	84.15	607
GOV	13	47.54	86.39	618
NGO	29	24.52	46.99	711

Note(s): (a) Note that due to unavailability of administrative data, we are unable to present distribution of schools per school-type in the greater population.

School Type and Selection: Sorting?

- Investigate selection across school-types in terms of 5 key variables :
  1. Monthly Family Expenditure (deflated by equivalence scale);
  2. Father's Schooling;
  3. Mother's Schooling;
  4. K-BIT (IQ/Fluid Intelligence);
  5. Raven's Coloured Progressive Matrices (IQ/Fluid Intelligence).

School Type and Selection: Sorting? (cont'd)

- 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';
  - K-BIT and Raven's CPM - 2 different IQ tests that have some overlap (but not full overlap).
  - Essentially K-BIT has some questions that are similar to Raven's but also has some additional questions (not present in the Raven's).

Selection: Means Across School-types for Boys

Table 2: Means Across School-Types (Boys)

	JAAGO	GOV	NGO
Monthly Family Expdt	5.8423	6.2623	5.4401
(in BDT 1000 adjusted by equivalence scale)	(0.1878)	(0.1459)	(0.1247)
Father's schooling	4.0212	3.8987	3.0961
	(0.2671)	(0.2597)	(0.3139)
Mother's schooling	3.7327	3.2368	2.6275
	(0.2503)	(0.2211)	(0.2263)
Raven's CPM (IQ)	0.2635	0.2031	-0.2510
	(0.1473)	(0.0859)	(0.0781)
K-BIT (IQ)	0.3596	0.0412	-0.3100
	(0.0791)	(0.0519)	(0.1041)
Observations	260	278	281

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

Selection: Means Across School-types for Girls

Table 3: Means Across School-Types (Girls)

	JAAGO	GOV	NGO
Monthly Family Expdt	5.8470	6.0575	5.3159
(in BDT 1000 adjusted by equivalence scale)	(0.1276)	(0.1280)	(0.1018)
Father's schooling	3.3787	3.5254	2.8093
	(0.2049)	(0.2500)	(0.2441)
Mother's schooling	3.8481	3.2624	2.5185
	(0.1943)	(0.2876)	(0.1874)
Raven's CPM (IQ)	0.0443	0.0302	-0.2285
	(0.1089)	(0.0735)	(0.0576)
K-BIT (IQ)	0.1858	0.0875	-0.2913
	(0.1018)	(0.0921)	(0.0768)
Observations	316	308	360

Notes: (a) Standard errors in parentheses clustered at the street level; (b) For the IQ scores, we use their respective 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 σ_a is the mean and standard deviation in age group a.

Selection: Mean Differences Across School-types for Boys

Table 4: Mean Differences Across School-Types for Boys

	(1) J vs G	(2) J vs N	(3) G vs N
Monthly Family Expdt	-0.4200**	0.4021*	0.8222***
(in BDT 1000 adjusted by equivalence scale)	(0.1851)	(0.2096)	(0.1765)
Father's Schooling	0.1225	0.9251*	0.8026*
	(0.3275)	(0.4746)	(0.4151)
Mother's Schooling	0.4959*	1.1052***	0.6093**
	(0.2598)	(0.2931)	(0.2888)
Raven's CPM (IQ)	0.0604	0.5145***	0.4541***
	(0.1636)	(0.1552)	(0.1037)
K-BIT (IQ)	0.3184***	0.6696***	0.3512***
	(0.0869)	(0.1275)	(0.0995)
Observations	538	541	559

Notes: (a) Bootstrapped 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 both the IQ scores, we report their respective age adjusted Z-scores.

Selection: Mean Differences Across School-types for Girls

Table 5: Mean Differences Across School-Types for Girls

	(1) J vs G	(2) J vs N	(3) G vs N
Monthly Family Expdt	-0.2105	0.5311***	0.7416***
(in BDT 1000 adjusted by equivalence scale)	(0.1629)	(0.1303)	(0.1537)
Father's Schooling	-0.1467	0.5694**	0.7162**
	(0.2665)	(0.2899)	(0.3276)
Mother's Schooling	0.5857*	1.3296***	0.7439**
	(0.3393)	(0.2138)	(0.3168)
Raven's CPM (IQ)	0.0141	0.2728***	0.2587***
	(0.1109)	(0.0983)	(0.0928)
K-BIT (IQ)	0.0983	0.4771***	0.3788***
	(0.1243)	(0.1184)	(0.1164)
Observations	624	676	668

Notes: (a) Bootstrapped 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 both the IQ scores, we report their respective age adjusted Z-scores.

Evidence of Selection Across School-Types

- J vs. G (both genders)
  - Boys at GOV schools belong to wealthier families.
  - Both genders at JAAGO schools have better educated mothers.
  - Boys with higher K-BIT score (fluid intelligence) go to JAAGO schools.
  - Raven's test score (fluid intelligence) fails to pick up any significant difference between JAAGO and GOV students for both genders.
- J vs. N and G vs. N (both genders)
  - NGO boys and girls have significantly lower fluid intelligence, have less educated parents and belong to poorer families.

Outcome Variable

- Our outcome variable: Woodcock Johnson Tests 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 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 and NGO students; administered the same tests to JAAGO students in "Banglish" (i.e. kept technical terms in English).

Methodology: Dealing with Selection

- To gain intuition, consider a regression model for school achievement;
  - School-type is endogenous - children with different observed and unobserved abilities & family background sort into different school-types.
  - Simple Estimation Equation

$$Ach_i = c + \gamma\, Male_i + \alpha_1\, DJ_i + \alpha_2\, DN_i$$
$$+\beta_1\, [DJ_i\, \times\, Male] + \beta_2\, [DN_i\, \times\, Male] + \epsilon_i$$

where:

- Ach_i: child's z-score in the Woodcock Johnson Test;
- GOV schools (female) are the reference group;
- $DJ_i = 1\, if\, JAAGO, 0\, otherwise$; $DN_i = 1\, if\, NGO, 0\, otherwise.$

Methodology: Dealing with Endogeneity

- Due to selection, we are worried that:
  - $cov\,(DN_i,\,\epsilon_i)\,\neq 0,\,cov\,(DJ_i,\,\epsilon_i)\,\neq 0;$
  - $cov\,(DN_i\,\times\,Male,\,\epsilon_i)\,\neq 0, cov\,(DJ_i\,\times\,Male,\,\epsilon_i)\,\neq 0.$
- One way to deal with this selection problem - use the Instrumental Variable Approach;
- However, we do not use this approach because:
  - IV estimates are inconsistent in the presence of choice based sampling [Solon et al. (2015)].
  - Adjusting IV estimator to make it consistent infeasible given our sample.

Matching: Least Squares Version

- We will deal with our selection issue by assuming that there exists observable X, such that conditional on X, what school-type they go to is a coin toss.
  - This is called the Conditional Independence Assumption (CIA).
  - It is not clear that the Least Squares approach works with Choice Based Sampling, but it is useful expositionally.

Methodology: Least Squares Version (cont'd)

- Given CIA we can run OLS with X as regressors where X consists of family background and fluid intelligence:

$$Ach_i = c + \gamma\, Male_i + \alpha_1\, DJ_i + \alpha_2\, DN_i + \delta\, X_i$$
$$+\beta_1\, [DJ_i \times Male_i] + \beta_2\, [DN_i \times Male_i] + \nu_i$$

Regression Estimates: Coefficients of Interest

- Coefficients of Interest for Across School-Type Comparisons by Gender:
  - J vs. G (girls): α_1
  - G vs. N (girls): $-\alpha_2$
  - J vs. N (girls): $\alpha_1 - \alpha_2$
  - J vs. G (boys): $\alpha_1 + \beta_1$
  - G vs. N (boys): $-\alpha_2 - \beta_2$
  - J vs. N (boys): $\alpha_1 + \beta_1 - \alpha_2 - \beta_2$
- Coefficients of Interest for Within School-Type Comparisons by Gender:
  - Boys vs. Girls (JAAGO): $\gamma + \beta_1$
  - Boys vs. Girls (GOV): γ
  - Boys vs. Girls (NGO): $\gamma + \beta_2$

OLS Tables

Regression Estimates: Coefficients of Interest (cont'd)

- However, even in the absence of Choice Based Sampling, OLS essentially compares all treatment to all comparisons and imposes strong functional form assumptions.
- Additionally, there no proof that OLS conditional on X is consistent given Choice Based Sampling.

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

- Our IQ measures are intended to measure:
  - *fluid* intelligence (i.e. intelligence not affected by schooling) and NOT *crytallized* intelligence, as shown by Blair and Razza (2007); Fitzpatrick et al. (2014); Swanson (2008, 2011); Dauvier et al. (2014); Font (2014); Barac and Bialystok (2012); Hastings et al. (2014).
  - It is possible to improve Raven's score by teaching to the test; however, such training is not common in the average slum schools of Bangladesh.
  - Raven's and K-BIT scores tend to increase by age; to account for this, we normalize each score by age.

What if school-type affects IQ?

- Suppose schooling does affect IQ, and better school types raise IQ more.
  - Then it is straight-forward to show our J vs N and G vs N 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? (cont'd)

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

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

- We estimate:

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

or,

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

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

Alternatively Use Propensity Score Matching

- Another way to control for this selection:
  - Compare school-type 1 to school-type 2 using Propensity Score Matching which can be adjusted for Choice Based Sampling.
  - Consider 3 Treatment Effects:
    - Average Treatment on the Treated (ATT);
    - Average Treatment on the Untreated (ATU);
    - Average Treatment Effect (ATE) [today's focus]
- For expository purposes, in what follows, we let the JAAGO individuals be the treatment students and NGO individuals be the comparison students.

Use Propensity Score Matching to Obtain Treatment Effects

- Average Treatment Effect on the Treated (ATT)
  - ATT captures the average effect, on achievement, of taking all students attending JAAGO schools and placing them in NGO schools.
- Average Treatment Effect on the Untreated (ATU)
  - ATU captures the average effect, on achievement, of taking all students attending NGO schools and placing them in JAAGO schools.
- Average Treatment Effect (ATE)
  - We can aggregate the ATT and ATU to get the ATE;
  - ATE is the effect, on achievement, of switching a randomly chosen student from JAAGO schools to NGO schools (or vice versa with a change of sign).

Defining Treatment Effects: ATT and ATU

- Specifically, we get ATT by comparing each child i in JAAGO with propensity score $P_1(X_i)$ to NGO observations j with similar propensity scores $P_1(X_j)$, where $P_1(X)$ is the probability of going to JAAGO schools versus NGO schools given characteristics X.

- Then, we get ATU by comparing each child j in NGO with propensity score $P_2(X_j)$ to JAAGO observations i with similar propensity scores $P_2(X_i)$, where $P_2(X)$ is the probability of going to NGO schools versus JAAGO schools given characteristics X.

- We use local linear matching to obtain the ATT and ATU.

Local Linear Regression Matching

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

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

  where
  - $K(.)$ is the kernel weighting function;
  - h is the bandwidth;
  - j refers to NGO students whose total number is N_2.
- We impose the common support condition $0 < p(x_i) < 1$.

Trimming, Bandwidth Choice and Kernel Type

Local Linear Regression Matching (cont'd)

- 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 JAAGO;
- $\widehat{Y_{0i}}$: predicted test score of JAAGO child i if s/he had gone to NGO; note that the minimization problem on the previous slide yields $\widehat{\beta}_{0i}=\widehat{Y_{0i}}$ as the counterfactual estimate of each JAAGO student i.

Local Linear Regression Matching (cont'd)

- When estimating the ATU, local linear regression matching methods construct the counterfactual by solving the following minimization problem for each NGO student j and setting the counterfactual to $\widehat{\alpha}_{0j} = \widehat{Y_{1j}}$:

$$\min_{\alpha_0,\alpha_1} \sum_{i=1}^{N_1} \left\{ Y_i - \alpha_{0j} - \alpha_{1j}\left[\hat{p}(x_i) - p_j\right] \right\}^2 K\Big(\frac{\hat{p}(x_i) - p_j}{h}\Big)$$

  where
  - $K(.)$ is the kernel weighting function;
  - h is the bandwidth;
  - i refers to JAAGO students whose total number is N_1.
- We impose the common support condition $0 < p(x_j) < 1$.

Local Linear Regression Matching (cont'd)

- The Average Treatment Effect on the Untreated (ATU) is:

$$\frac{1}{N_2}\sum_{D_j=0}(\widehat{Y_{1j}} - Y_{0j}) = \frac{1}{N_2}\sum_{D_j=0}(\widehat{Y_{1j}}) - \frac{1}{N_2}\sum_{D_j=0}(Y_{0j})$$

  - Y_{0j} : observed test score of child j going to NGO;
  - $\widehat{Y_{1j}}$: predicted test score of NGO child j if s/he had gone to JAAGO; note that the minimization problem on the previous slide yields $\widehat{\alpha}_{0j} = \widehat{Y_{1j}}$ as the counterfactual estimate of each NGO student j.

Local Linear Matching (cont'd)

- We combine the ATT and the ATU to obtain the ATE;
- Recall that ATE refers to the effect, on achievement, of switching a randomly chosen student from JAAGO schools to NGO schools (or vice versa with a change of sign).
- Note that we need similarly sized treatment and comparison groups to obtain a relatively precise ATE; which is another reason to use our sampling approach.

Propensity Score Matching (with Choice Based Sampling)

- Do matching while accounting for choice based sampling;
  - However, with choice based sampling, standard propensity score matching does not yield consistent estimates;
  - This problem can be addressed by the Heckman and Todd (2009) approach;
    - Match on log odds ratio (LOR) of the estimated propensity score to obtain consistent estimates.
    - Note that LOR replaces p in the previous slides.
- Note that for the treatment effects, we use bootstrapped standard errors clustered at the street level.

Trimming, Bandwidth Choice and Kernel-Type

- We need to trim the data to achieve common support.
  - Continuing with the example of *J vs. N* students, we do not want to estimate the ATT for *J vs. N* where there are no N students.
  - Similarly, we do not want to estimate ATU for *J vs. N* where there are no J students.

- Note that the distribution of the LOR's are similar across treatments and controls, especially in the tails.

- We use 2 methods to obtain common support and I can talk about them after my presentation.

Trimming, Bandwidth Choice and Kernel-Type (cont'd)

- When choosing the bandwidth, we again use 2 alternative approaches - one of which is a fixed ex-ante bandwidth, while the other bandwidth is data driven.
- Bandwidth choice is considered important in this literature.
- The data driven approach of bandwidth choice is supposed to be optimal (but it is optimal for LLR, not LLR matching).
- We also use a Normal Kernel and an Epanechnikov Kernel.
- Our results are quite robust to all these choices.

Local Linear Matching

Estimating ATE using Zero Drop Rule Method of Trimming, Data Driven Bandwidth and Epanechnikov Kernel

Table 6: **Estimating ATE using Matching to Control for Selection (Zero Drop Rule Method of Trimming and Data Driven Bandwidth using Epanechnikov Kernel)**

	Dependent Variable - Achievement Test Z-Score					
	Under-12 Sample					Full Sample
	(1) **Mean Difference (no controls)**	(2) **Only Family Background (no IQ)**	(3) **Family Background and Raven's**	(4) **Family Background and K-BIT**	(5) **Family Background and Both IQ**	(6) **Family Background and K-BIT**
J vs. G (girls)	0.2459***	0.2305***	0.2295***	0.1924**	0.1986**	0.1933**
	(0.0752)	(0.0863)	(0.0848)	(0.0838)	(0.0850)	(0.0767)
bandwidth		0.21	0.24	0.24	0.30	0.23
J vs. G (boys)	0.1201	0.1241	0.1204	-0.0038	0.0145	-0.0209
	(0.0880)	(0.1049)	(0.0870)	(0.0963)	(0.0870)	(0.0884)
bandwidth		0.46	0.34	0.22	0.25	0.23
J vs. N (girls)	0.4937***	0.4566***	0.4059***	0.2969***	0.2833***	0.2718***
	(0.0931)	(0.0911)	(0.1043)	(0.0883)	(0.0951)	(0.0822)
bandwidth		0.70	0.38	0.36	0.34	0.45
J vs. N (boys)	0.5754***	0.4968***	0.3569***	0.2308*	0.2205*	0.2027*
	(0.1457)	(0.1297)	(0.1272)	(0.1378)	(0.1328)	(0.1229)
bandwidth		0.31	0.43	0.36	0.54	0.52
G vs. N (girls)	0.2477***	0.1969***	0.0950	0.0322	0.0160	0.0050
	(0.0949)	(0.0989)	(0.0988)	(0.1003)	(0.0942)	(0.0965)
bandwidth		0.43	0.46	0.42	0.46	0.52
G vs. N (boys)	0.4554***	0.4001***	0.2518**	0.3055**	0.2072*	0.2790**
	(0.1175)	(0.1249)	(0.1204)	(0.1188)	(0.1132)	(0.1107)
bandwidth		0.29	0.38	0.40	0.55	0.56

Notes: (a) Bootstrapped standard errors in parentheses clustered at the street level; (b) We report Average 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 4 and 5.

Detailed Matching Results with Both IQ Measures for Table 6

Table 7: Detailed Matching Results with Both IQ Measures for Table 6

	(1) J vs G (F)	(2) J vs G (M)	(3) J vs. N (F)	(4) J vs. N (M)	(5) G vs. N (F)	(6) G vs. N (M)
ATT	0.1763*	0.0269	0.1543	0.1900	-0.0219	0.1445
	(0.0944)	(0.0916)	(0.1018)	(0.1229)	(0.0976)	(0.1171)
ATU	0.2217***	0.0029	0.3960***	0.2494	0.0489	0.2732*
	(0.0835)	(0.0959)	(0.0914)	(0.1543)	(0.1057)	(0.1398)
ATE	0.1986**	0.0145	0.2833***	0.2205*	0.0160	0.2072*
	(0.0850)	(0.0870)	(0.0951)	(0.1328)	(0.0942)	(0.1132)

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 4 and 5.

Estimating ATE using Common Method of Trimming, Rescaled Bandwidth and Epanechnikov Kernel

Table 8: **Estimating ATE using Matching to Control for Selection (Common Method of Trimming and Rescaled Bandwidth using Epanechnikov Kernel)**

	Dependent Variable - Achievement Test Z-Score					
	Under-12 Sample					Full Sample
	(1) **Mean Difference (no controls)**	(2) **Only Family Background (no IQ)**	(3) **Family Background and Raven's**	(4) **Family Background and K-BIT**	(5) **Family Background and Both IQ**	(6) **Family Background and K-BIT**
J vs. G (girls)	0.2459***	0.2228***	0.2227***	0.1964**	0.2053**	0.1835**
	(0.0710)	(0.0835)	(0.0815)	(0.0815)	(0.0837)	(0.0777)
bandwidth		0.10	0.10	0.12	0.13	0.12
J vs. G (boys)	0.1201	0.1106	0.1046	-0.0021	0.0247	-0.0225
	(0.0812)	(0.1034)	(0.0833)	(0.0969)	(0.0878)	(0.0876)
bandwidth		0.09	0.09	0.13	0.13	0.12
J vs. N (girls)	0.4937***	0.4637***	0.3951***	0.3011***	0.2852***	0.2402***
	(0.0712)	(0.0854)	(0.1033)	(0.0880)	(0.0943)	(0.0834)
bandwidth		0.21	0.20	0.21	0.21	0.28
J vs. N (boys)	0.5754***	0.5085***	0.3520***	0.2352*	0.2095	0.2069
	(0.0852)	(0.1325)	(0.1303)	(0.1386)	(0.1328)	(0.1260)
bandwidth		0.16	0.16	0.21	0.21	0.23
G vs. N (girls)	0.2477***	0.2008**	0.1087	0.0559	0.0463	0.0036
	(0.0789)	(0.0956)	(0.0987)	(0.1002)	(0.1011)	(0.0944)
bandwidth		0.19	0.21	0.23	0.24	0.26
G vs. N (boys)	0.4554***	0.4164***	0.2474**	0.2887**	0.2103*	0.2925**
	(0.0897)	(0.1259)	(0.1215)	(0.1199)	(0.1208)	(0.1136)
bandwidth		0.17	0.17	0.19	0.21	0.20

Notes: (a) Bootstrapped standard errors in parentheses clustered at the street level; (b) We report Average 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 4 and 5.

Average Treatment Effects for Different Bandwidths, Trimming Methods and Kernels (Both IQ Specification)

Table 9: **Average Treatment Effects for Different Bandwidths, Trimming and Kernel (Both IQ Specification)**

	Dependent Variable - Achievement Test Z-Score					
	(1.1) **Common and Rescaled Bandwidth (Epanechnikov)**	(1.2) **Common and Rescaled Bandwidth (Normal)**	(2.1) **Zero Drop Rule and Rescaled Bandwidth (Epanechnikov)**	(2.2) **Zero Drop Rule and Rescaled Bandwidth (Normal)**	(3.2) **Common and Data Driven Bandwidth (Epanechnikov)**	(4.2) **Zero Drop Rule and Data Driven Bandwidth (Epanechnikov)**
J vs. G (girls)	0.2053** (0.0837)	0.2117** (0.0841)	0.1935** (0.0821)	0.2031** 0.0835	0.2123** (0.0860)	0.1986** (0.0850)
bandwidth	0.13	0.13	0.11	0.11	0.49	0.30
J vs. G (boys)	0.0247 (0.0878)	0.0132 (0.0868)	0.0247 (0.0878)	0.0132 (0.0868)	0.0145 (0.0870)	0.0145 (0.0870)
bandwidth	0.13	0.13	0.13	0.13	0.25	0.25
J vs. N (girls)	0.2852*** (0.0943)	0.3096*** (0.0933)	0.2765*** (0.0952)	0.3016*** (0.0929)	0.2910*** (0.0940)	0.2833*** (0.0951)
bandwidth	0.21	0.21	0.23	0.23	0.28	0.34
J vs. N (boys)	0.2095 (0.1328)	0.2310* (0.1285)	0.2024 (0.1359)	0.2308* (0.1314)	0.2258* (0.1289)	0.2205* (0.1382)
bandwidth	0.21	0.21	0.23	0.23	0.58	0.54
G vs. N (girls)	0.0463 (0.1011)	0.0291 (0.0924)	0.0225 (0.0947)	0.0134 (0.0901)	0.0184 (0.1007)	0.0160 (0.0942)
bandwidth	0.24	0.24	0.20	0.20	0.40	0.46
G vs. N (boys)	0.2103* (0.1208)	0.1916 (0.1179)	0.2158* (0.1200)	0.1960* (0.1161)	0.1970* (0.1147)	0.2072* (0.1132)
bandwidth	0.21	0.21	0.20	0.20	0.56	0.55

Notes: (a) Bootstrapped standard errors in parentheses clustered at the street level; (b) We report Average 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 4 and 5.

Diagnostics

- Can we get a signal if matching is appropriate here, i.e., if the CIA holds - balancing tests.
- Given the propensity scores, look for a treatment effect on the $X's$ since we shouldn't see one.
  - Many ways of doing balancing tests, see, e.g. Smith and Todd (2005), Dehija (2005) etc;
  - Ours is another approach which has the advantages that it takes into account the fact that $p(X)$ is estimated and we do not use an 'eyeball' test.

Diagnostics (cont'd)

- Similar to obtaining the treatment effects, for the balancing tests we use local linear matching and adjust for the choice based sampling by matching on log odds ratio of the estimated propensity score.
- Note that we use the same trimmed sample, bandwidth and kernel-type in the balancing tests as in the matching exercises.
- The balancing tests again use bootstrapped standard errors clustered at the street level.
- Recall that, without matching, there are big differences in the conditioning variables, i.e. raw values do not balance.

Balancing Tests

Table 10: **Balancing Tests at the 5% level for Matching Estimators with Different Trimming Methods, Rescaled Bandwidth and the Epanechnikov Kernel**

	Matching using Common Method of Trimming and Rescaled Bandwidth		Matching using Zero Drop Rule Method of Trimming and Rescaled Bandwidth	
	(1) **LOR estimated using 7 covariates (including IQ)**	(2) **LOR estimated using 5 covariates (excluding IQ)**	(3) **LOR estimated using 7 covariates (including IQ)**	(4) **LOR estimated using 5 covariates (excluding IQ)**
J vs. G (girls)	0	0	0	0
J vs. G (boys)	0	1	0	1
J vs. N (girls)	0	2	0	2
J vs. N (boys)	0	2	0	2
G vs. N (girls)	0	2	0	2
G vs. N (boys)	0	2	0	2

Notes: (a) Log Odds Ratio (LOR) estimated using 5 covariates includes only family background matching covariates, i.e., child's age, family size, father absence dummy, father's schooling and mother's schooling; (b) Log Odds Ratio (LOR) estimated using 7 covariates includes the standard set of family background variables mentioned in (a) along with Raven's and K-BIT Z-scores.

Balancing Tests (cont'd)

Table 11: **Balancing Tests at the 5% level for Matching Estimators with Different Trimming Methods, Data Driven Bandwidth and the Epanechnikov Kernel**

	Matching using Common Method of Trimming and Data Driven Bandwidth		Matching using Zero Drop Rule Method of Trimming and Data Driven Bandwidth	
	(1) **LOR estimated using 7 covariates (including IQ)**	(2) **LOR estimated using 5 covariates (excluding IQ)**	(3) **LOR estimated using 7 covariates (including IQ)**	(4) **LOR estimated using 5 covariates (excluding IQ)**
J vs. G (girls)	0	0	0	0
J vs. G (boys)	0	1	0	1
J vs. N (girls)	0	2	0	2
J vs. N (boys)	0	2	0	2
G vs. N (girls)	0	2	0	2
G vs. N (boys)	0	2	0	2

Notes: (a) Log Odds Ratio (LOR) estimated using 5 covariates includes only family background matching covariates, i.e., child's age, family size, father absence dummy, father's schooling and mother's schooling; (b) Log Odds Ratio (LOR) estimated using 7 covariates includes the standard set of family background variables mentioned in (a) along with Raven's and K-BIT Z-scores.

Balancing Tests for Matching Covariates

- Results
  - We pass the balancing test for all variables when we use the full model to estimate the propensity score;
  - On the other hand, if we use only family background variables (excluding IQ) to estimate the propensity score, we fail the balancing test for variables like Raven's and K-BIT.

Estimating Within School-Type Gender Differences

- We also estimate gender differences in achievement within each school-type.
- Taking the example of Boys vs. Girls at NGO schools, when estimating the ATT, local linear regression matching methods construct the counterfactual by solving the following minimization problem for each NGO boy i and setting the counterfactual to $\widehat{\delta_{0i}} = \widehat{Y_{0i}}$:

$$\min_{\delta_0,\delta_1} \sum_{j=1}^{N_2} \left\{ Y_j - \delta_{0i} - \delta_{1i}\left[\hat{l}(x_j) - l_i\right] \right\}^2 K\Big(\frac{\hat{l}(x_j) - l_i}{h}\Big)$$

where

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

Estimating Within School-Type Gender Differences (cont'd)

- For Boys vs. Girls (NGO), 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 boy i going to NGO;
- $\widehat{Y_{0i}}$: predicted test score of a comparable girl i at NGO schools; note that the minimization problem on the previous slide yields $\widehat{\delta}_{0i} = \widehat{Y_{0i}}$ as the counterfactual estimate of each NGO boy i.

Local Linear Matching (cont'd)

- Similarly, we estimate the Average Treatment Effect on the Untreated (ATU) where we now treat girls at NGO schools as the Treatment Group;
- As before, we combine the ATT and the ATU to obtain the ATE.

Average Treatment Effects for Within School-Type Differences between Boys and Girls using Matching

Table 12: **Within School-type Differences between Boys and Girls Controlling for Observables using Propensity Score Matching**

	Dependent Variable - Achievement Test Z-Score		
	(1.1) **Common and Rescaled Bandwidth (Epanechnikov)**	(1.2) **Common and Rescaled Bandwidth (Normal)**	(3.2) **Common and Data Driven Bandwidth (Epanechnikov)**
Boys vs. Girls (JAAGO)	0.0648	0.0664	0.0620
	(0.0741)	(0.0751)	(0.0751)
bandwidth	0.09	0.09	0.16
Boys vs. Girls (GOV)	0.2502***	0.2593***	0.2544***
	(0.0785)	(0.0809)	(0.0796)
bandwidth	0.07	0.07	0.25
Boys vs. Girls (NGO)	0.0795	0.0945	0.0797
	(0.0740)	(0.0723)	(0.0722)
bandwidth	0.04	0.04	0.11

Notes: (a) Bootstrapped standard errors in parentheses clustered at the street level; (b) We report Average Treatment Effects at the 1 percent, 5 percent and 10 percent significance level denoted by *** , ** , and * respectively; (c) Matching covariates consists of child's age, family size, father absence dummy, father's schooling, mother's schooling, Raven's and K-BIT IQ tests; (d) For sample size, refer to Tables 2 and 3.

Key Findings

- Students in urban slums of Dhaka sorted across school-types.
  - 'Better' students sorted into JAAGO and government schools;
  - 'Weaker' students sorted into NGO schools.
- Fluid Intelligence plays a crucial part in controlling for selection.
  - Including fluid intelligence, especially K-BIT, which most developing country studies fail to account for, substantially reduces bias.
  - Note that K-BIT plays a larger role in reducing selection bias than Raven's.
- Family Background does not play much of a role in controlling for selection.

Key Findings (cont'd)

- Matching Results are insensitive to changing the trimming, bandwidth or kernel when doing Local Linear Regression Matching.
- Our sampling design allowed us to obtain relatively precise estimates when adopting good econometric practice. We took this econometric practice into account when collecting our data.
- Our empirical models pass balancing tests; it seems like these tests have some power.

Key Findings (cont'd)

- Boys and girls are differentially affected across the 3 school-types:
  - GOV vs. NGO: Boys are better off at GOV schools, but girls perform equally well at both school-types.
  - JAAGO vs. GOV: Girls are better off at JAAGO, but boys perform equally well at both school-types.
  - JAAGO vs. NGO: Both genders better off at JAAGO.

Key Findings (cont'd)

- When we compare boys and girls within each school-type:
  - No difference in achievement between boys and girls at JAAGO or NGO schools;
  - But boys do significantly better than girls at GOV Schools.
- School-types like JAAGO could reduce the gender gap in achievement.
  - If all girls going to GOV schools could switch to JAAGO, gender gap would fall substantially.

Understanding the Gender Heterogeneity (Across School-Type Comparisons)

- What school-type characteristics may be driving the gender difference in achievement between JAAGO and GOV schools?
  - Pro-male gender bias at GOV schools;
  - Share of female teachers lower at GOV schools;
  - Corporal punishment common at GOV schools.

- Find evidence of a gender differential for all above components in the literature.

Thank You

Distributions of Schools by School Type in Our Under-12/ Smaller Sample

Table 13: **Summary Statistics of Schools by School Type (Under-12/ Smaller Sample)**

	(1) No. of schools	(2) Mean (no. of students)	(3) Std. Dev	(4) Total (no. of students)
JAAGO	2	288	80.61	576
GOV	13	45.08	81.71	586
NGO	28	22.89	43.80	641

Notes: (a) that due to unavailability of administrative data, we are unable to present distribution of schools per school-type in the greater population. (b) By smaller sample, we refer to students aged between 5 years and 11 years and 11 months for whom the Raven's CPM IQ test is designed.

Estimating ATE using Common Method of Trimming, Data Driven Bandwidth and Epanechnikov Kernel

Table 14: **Estimating ATE using Matching to Control for Selection (Common Method of Trimming and LPOLY Bandwidth using Epanechnikov Kernel)**

	Dependent Variable - Achievement Test Z-Score					
	Under-12 Sample					Full Sample
	(1) **Mean Difference (no controls)**	(2) **Only Family Background (no IQ)**	(3) **Family Background & Raven's**	(4) **Family Background & K-BIT**	(5) **Family Background & Both IQ**	(6) **Family Background & K-BIT**
J vs. G (girls)	0.2459***	0.2252***	0.2234***	0.1902**	0.2123**	0.1843**
	(0.0752)	(0.0850)	(0.0827)	(0.0842)	(0.0860)	(0.0793)
bandwidth		0.23	0.25	0.28	0.49	0.25
J vs. G (boys)	0.1201	0.1194	0.1183	-0.0026	0.0145	-0.0209
	(0.0880)	(0.1040)	(0.0851)	(0.0961)	(0.0870)	(0.0879)
bandwidth		0.42	0.33	0.22	0.25	0.23
J vs. N (girls)	0.4937***	0.4685***	0.4012***	0.3057***	0.2910***	0.2490***
	(0.0931)	(0.0875)	(0.1042)	(0.0877)	(0.0940)	(0.0829)
bandwidth		0.44	0.44	0.27	0.28	0.36
J vs. N (boys)	0.5754***	0.5096***	0.3497***	0.2322*	0.2258*	0.2044
	(0.1457)	(0.1311)	(0.1273)	(0.1382)	(0.1289)	(0.1248)
bandwidth		0.23	0.34	0.34	0.58	0.41
G vs. N (girls)	0.2477***	0.1935**	0.1106	0.0376	0.0184	0.0048
	(0.0949)	(0.0989)	(0.0990)	(0.1004)	(0.1007)	(0.0956)
bandwidth		0.41	0.43	0.42	0.40	0.50
G vs. N (boys)	0.4554***	0.3981***	0.2276**	0.2828**	0.1970*	0.2695**
	(0.1175)	(0.1249)	(0.1129)	(0.1159)	(0.1147)	(0.1092)
bandwidth		0.37	0.50	0.43	0.56	0.70

Notes: (a) Bootstrapped standard errors in parentheses clustered at the street level; (b) We report Average 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 4 and 5.

Estimating ATE using Zero Drop Rule Method of Trimming, Rescaled Bandwidth and Epanechnikov Kernel

Table 15: **Estimating ATE using Matching to Control for Selection (Zero Drop Rule Method of Trimming and Rescaled Bandwidth using Epanechnikov Kernel)**

	Dependent Variable - Achievement Test Z-Score					
	Under-12 Sample					Full Sample
	(1) **Mean Difference (no controls)**	(2) **Only Family Background (no IQ)**	(3) **Family Background & Raven's**	(4) **Family Background & K-BIT**	(5) **Family Background & Both IQ**	(6) **Family Background & K-BIT**
J vs. G (girls)	0.2459***	0.2296***	0.2280***	0.1931**	0.1935**	0.1990***
	(0.0752)	(0.0854)	(0.0835)	(0.0815)	(0.0821)	(0.0756)
bandwidth		0.11	0.11	0.11	0.11	0.12
J vs. G (boys)	0.1201	0.1180	0.1112	-0.0005	0.0247	-0.0207
	(0.0880)	(0.1042)	(0.0850)	(0.0971)	(0.0878)	(0.0879)
bandwidth		0.10	0.10	0.13	0.13	0.12
J vs. N (girls)	0.4937***	0.4565***	0.4002***	0.2877***	0.2765***	0.2629***
	(0.0931)	(0.0870)	(0.1033)	(0.0891)	(0.0952)	(0.0821)
bandwidth		0.20	0.20	0.24	0.23	0.28
J vs. N (boys)	0.5754***	0.5040***	0.3607***	0.2309*	0.2024	0.2038
	(0.1457)	(0.1332)	(0.1323)	(0.1388)	(0.1359)	(0.1271)
bandwidth		0.15	0.17	0.23	0.23	0.24
G vs. N (girls)	0.2477***	0.1987**	0.0992	0.0375	0.0225	0.0052
	(0.0949)	(0.0953)	(0.1019)	(0.0989)	(0.0947)	(0.0959)
bandwidth		0.18	0.23	0.21	0.20	0.23
G vs. N (boys)	0.4554***	0.4093***	0.2544**	0.3105**	0.2158*	0.2981***
	(0.1175)	(0.1250)	(0.1253)	(0.1234)	(0.1200)	(0.1157)
bandwidth		0.17	0.16	0.21	0.20	0.19

Notes: (a) Bootstrapped standard errors in parentheses clustered at the street level; (b) We report Average 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 4 and 5.

Regressions Matching Using Both IQ Measures (Across and Within School-Type Comparisons)

Table 16: **Regressions Matching Using Both IQ Measures (Across and Within School-Type Comparisons)**

(a) **Regressions Matching with Both IQ**

Dependent Variable - Achievement Test Z-Score	
	Family Background & Both IQ
JAAGO	0.2122** (0.0803)
NGO	-0.0460 (0.0942)
JAAGO X Male	-0.2117* (0.1125)
NGO X Male	-0.1834* (0.0961)
Age (years)	0.0073 (0.0168)
Male	0.2445*** (0.0716)
Father absent	-0.2061** (0.0947)
Family Size	0.0156 (0.0221)
Father's schooling	0.0228*** (0.0058)
Mother's schooling	0.0157** (0.0067)
Raven's CPM (IQ)	0.1811*** (0.0232)
K-BIT (IQ)	0.3268*** (0.0274)
Constant	-0.3594* (0.1963)

Notes: (a) Standard errors in parentheses clustered at the street level; (b) We report estimates at the 1 percent, 5 percent and 10 percent significance level denoted by *** , ** , and * respectively; (c) We present the results for the specification on slide 32 in this table with estimations of across and within school-type comparisons in tables 16b and 16c;

(b) **Summary of Regression Coefficients: Across School-type Comparisons**

	Family Background & Both IQ
J vs G (girls)	0.2122** (0.0803)
J vs. G (boys)	0.0005 (0.0825)
J vs. N (girls)	0.2582*** (0.0876)
J vs. N (boys)	0.2300* (0.1286)
G vs N (girls)	0.0460 (0.0942)
G vs. N (boys)	0.2294* (0.1219)

Notes: (a) Standard errors in parentheses clustered at the street level; (b) We report estimates at the 1 percent, 5 percent and 10 percent significance level denoted by *** , ** , and * respectively; (c) This table is derived from Table 16a; school-type effects for the six comparison cases is calculated from the estimated coefficients of Table 16a.

(c) **Summary of Regression Coefficients: Within School-type Comparisons**

	Family Background & Both IQ
Boys vs. Girls (JAAGO)	0.0328 (0.0750)
Boys vs. Girls (GOV)	0.2445*** (0.0716)
Boys vs. Girls (NGO)	0.0611 (0.0702)

Notes: (a) Standard errors in parentheses clustered at the street level; (b) We report estimates at the 1 percent, 5 percent and 10 percent significance level denoted by *** , ** , and * respectively; (c) This table is derived from Table 16a; within school-type gender difference is calculated from the estimated coefficients of Table 16a.

Back: Coefficients of Interest