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Why do students learn more in some classrooms than in others? Evidence from Bogotá

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Abstract

Many studies have documented that children in some classrooms learn considerably more than children who spend the year in other classrooms at the same grade level. It has proven difficult, however, to determine the extent to which differences in student achievement across classrooms stem from differences in the quality of teachers, the quality of peer groups, class sizes, and governance structures (public versus private). Using a unique data set providing longitudinal achievement data for a large sample of students who attended public or private elementary schools in Bogotá, Colombia, we examine the roles of teacher quality, class size, peer groups, and governance structure in predicting why, net of family background and prior achievement, the average achievement of children in some classrooms is much higher than that of children in other classrooms.

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I. Introduction

Over the last 35 years many studies have documented that students in some classrooms learn more, on average, than do students in other classrooms at the same grade level.[1] Researchers have typically attributed these differences to differences in teacher quality. However, little direct evidence supports this interpretation over potentially complementary alternatives such as differences in peer groups or class sizes. Nor is there much direct evidence on the related question of whether teachers are equally effective with different groups of students.

A companion literature has examined the relative effectiveness of public and private schools. Some studies have found private schools to be more effective than public schools; others have not. The lack of consensus is not surprising because the quality of public schools and private schools in particular samples vary as a result of differences in resource levels and differences in the institutional rules under which they operate. While the number of studies comparing public and private schools has grown, most suffer from two limitations. First, they treat schools as black boxes, and do not seek to explore whether public schools and private schools differ in critical dimensions that contribute to differences in effectiveness. Second, they do not explore the extent to which there is variation in school quality among schools in each sector. This is critical because the greater the variation in quality among schools in a sector relative to the difference in average quality between sectors, the less important is the decision about which sector to enroll a child in and the more important is the decision about which school within a sector to enroll a child in.

This study uses a new data set containing information on students and teachers in public and private elementary schools in Bogotá, Colombia to examine the reasons student achievement, net of family background and prior achievement, is higher in some fifth grade classrooms than in others. We make use of an unusual property of the data to disentangle the roles of teacher quality, peer groups, and class size. We show that all three have significant effects on student achievement. We also show that the average attributes of public schools and private schools differ markedly in dimensions that affect student achievement. Finally we show

[1] Hanushek 1971, 1992, 1995, 2002; Murnane and Phillips, 1981; Harbison and Hanushek, 1992; Mullens, Murnane and Willett, 1996; Rockoff, 2003.

that differences in quality among public schools and especially among private schools are much larger than the difference between the average quality of public and private schools.

II. The Bogotá Setting

Bogotá, the capital of Colombia, has a population of approximately 7 million. Approximately one third of households live on a per-capita income of $1.50 or less per day (Vergara, et al. 1997). Since the 1950s, the city has experienced a six-fold growth in population as migrants stream into the city in search of better economic opportunities or a safe refuge from the armed conflict that ravages large parts of the country.

More than 1.5 million students are enrolled in primary and secondary schools in Bogotá, the largest school district in the country.[2] Access and quality are both problems for the city's schools. In the mid-1990s more than 125,000 students from low income families did not attend school (SED, 2000). Of every 100 students who entered the first grade, only 58 graduated from high school, and only 27 of these did so in the expected number of years (SED, 2001).

Teachers

In the years to which our data pertain (1999-2001), government regulations required public school teachers to be certified before entering the teaching profession.[3] To be certified to teach primary school, teachers must have obtained at least a degree from a normal school. Until these schools were reformed in the late 90s to offer post-secondary training, normal schools were secondary schools that offered pedagogical training during the junior and senior years. Although a diploma from a normal school gives teachers access to entry level positions in the public sector, the national salary schedule, which bases promotions primarily on experience and academic credentials, provides strong incentives for teachers to obtain additional formal educational credentials.

There are 14 steps in Colombia's teacher salary schedule. Table 1 presents the annual salaries of teachers by step for the year 2000. Teachers can move from one step to the next based on years of experience, academic degrees, credits obtained through in-service courses approved by the Ministry of Education, and through publishing articles or books. Teachers who entered the

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[2] Mary Simpson, Director of Bogotá's Department of Education Planning Office, provided most of the statistical information on education in Bogotá.

[3] New legislation (Decree 1278, June 19th 2002) now allows non-educators to teach in public schools, provided they are selected through a competitive process and enroll in courses in pedagogy.

profession before 1979 without a teaching certificate but with at least a high school diploma were assimilated into grades 1-8 according to their years of experience. From 1979 onwards, primary school teachers in Bogotá and other cities must have a pedagogical high-school degree. Teachers with a pedagogical high school diploma start on step 1 of the salary schedule. “Specialists” in education (1-year post-secondary education program) start on step 2. Educational technology graduates (2 or 3-years post secondary) start on step 5. University graduates with a non–education diploma and an entering course in pedagogy begin on step 6. Graduates with a four-year degree in education (licensure) begin on step 7. Additional degrees, courses and years of experience allow teachers to climb steps in the ladder accordingly. In theory, only experienced teachers with a graduate degree and/or scientific, pedagogical or technical publications can reach Step 14 (Decreto Ley 2277, September 14th, 1979).

<< insert Table 1 here>>

As a result of the incentives built into the national teacher salary schedule, most public primary school teachers in Bogotá have four-year degrees in education and post-graduate training (based on data from Sarmiento, et al., 1999). As a result of relatively low turnover (3% annually) among Bogotá public school teachers and restrictions on the opening of new teaching posts in the public sector, the public school teaching force is mostly middle-aged and experienced, and relatively costly.[4]

In recent years in Colombia, an uncontrolled growth in salary obligations to teachers resulting from the current salary scale and benefits structure[5] and skepticism regarding the relationship between teacher pay and performance have placed the teacher compensation system under intense scrutiny. A related concern is the difficulty of dismissing poor-performing teachers. In the words of one analyst, the public school teacher tenure system “ensures that bad

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[4] New regulations that came into effect in 2002 introduce performance accountability mechanisms for promotions and reduce the weight of academic credentials and experience in determining promotions. These changes are likely to bring about changes in the city’s teaching force over the coming years.

[5] Annual increases in teacher salary obligations for this concept are estimated by the Ministry of Education to be close to a 5% in real terms (Margarita Peña, Bogotá’s Secretary of Education, personal communication).

teachers continue to teach because they cannot be let go" (Wolff and de Moura Castro, 2001, p.1).

Some see provision of educational services by private providers as a way to improve efficiency because the private sector's contracting system allows flexibility in the hiring and firing of teachers. This line of thought, shared by many of the top administrators in DOE, has shaped many of the policies introduced in Bogotá over the past few years.

Private Schools in Bogotá

In the year 2000, 53% of students in the city were enrolled in the city's 2,900 private schools.[6] For-profit schools, typically started by individuals, constitute 90 percent of all private schools in the city. The second most common type are religious schools, which make up 8 percent of the total. Most of these are Catholic and are sponsored by the Church. Traditionally they have been either subsidized or "contracted" by the State to provide educational services in low income areas. In Bogotá, religious organizations run both elite (unsubsidized), usually single sex schools, and subsidized schools in the most depressed neighborhoods serving the neediest population. A third type of private school consists of schools sponsored by Family Compensation Funds (*Cajas de Compensación Familiar).* These are funds established by associations of private industries and business to provide subsidized social services to employees (Villar, 1998). These funds are established from statutory payments of employers, amounting to 2-4% of the total payroll costs. In Bogotá, the seven schools sponsored with these funds are considered among the best equipped and most pedagogically innovative in the city (Villa and Duarte, 2002). Foundation-sponsored schools are a fourth type of non-public schools. They are founded by businesses or associations of individuals and are run by a board of directors. Many of the elite private schools in Bogotá are established as foundations. For legal and tax purposes, this mechanism requires that schools that make a profit have to reinvest it in the school. Finally, cooperative schools are established by neighborhood organizations typically in areas of unmet demand. They derive funding from both tuitions and public subsidies. Our sample includes 37 for-profit schools, nine religious schools, and one cooperative school.

[6] (SED, Boletín Estadístico, 2001). In the same year, 21% of all pre-university level students in the country were enrolled in private schools.

Under private contracting regulations (Código Sustantivo del Trabajo--CTS), private schools can hire teachers on a fixed-term basis and dismiss them when their services are no longer required. Furthermore, while private school teachers must generally meet the same certification requirements as public school teachers, they are allowed exceptions. For example, private schools may hire non-educators to teach specific disciplines or fields of study, provided the school takes responsibility for their pedagogical training (Article 198, 1991 Constitution).

Several large scale studies report that private school teachers in Bogotá have much less teaching experience and formal educational credentials than public school teachers (Sarmiento, et al., 1999; Gaviria et al., 2001). This pattern is also present in our data. There are three complementary explanations. First, as a result of a 1995 constitutional court ruling, private schools are required to pay teachers according to the public teacher salary scale. Second, in recent years a weak economy has made it difficult for many private schools to collect tuition payments and created great pressure to reduce operating costs. Third, government regulations restrict the rate of private school tuition increases to the rate of inflation, even for schools serving affluent families.

Private schools in Bogotá may set their own student admission policies, which are mostly based on academic criteria and/or on families' ability to pay. While, on average, private schools in Bogotá serve a more affluent segment of the population than do public schools, they enroll students from the whole range of the socio-economic spectrum. In fact, 43% of the private schools in our sample primarily enroll students from the lowest two socio-economic strata[7] (estrato 1& 2) while 10% enroll primarily students from the highest strata (estrato 4-6). In comparison, 75% of public schools in our sample enroll primarily students from the lowest two strata, and none enroll students from the upper income levels.

Another respect in which private schools differ from public schools is in the length of the school day. Most private schools in the city offer a "full" school day of 6 to 7 hours (SED, 2003), while almost all public schools have morning and afternoon shifts, making the school day for students in this sector approximately 2 hours shorter than in the private sector. In our sample, 62% of the private schools had full-day schedules while only one public school did.

[7] Bogotá has a six-level system of socio-economic stratification, with 6 as the highest and 1 as the lowest. Roughly, estrato 1 and 2 correspond to families earning up to two times the minimum wage (the 2003 minimum wage is approximately US$100/month). Estrato 4 and 5 families earn approximately between 5 to 10 times the minimum wage.

The yearly tuition fee for private schools in Bogotá in the 2002 school-year ranged from $30 to $2,400, with an average of $285 (SED, 2003). This is considerably less than the $439 average expenditure per student in public schools. However, these figures are not completely comparable because the public sector expenditure figure includes the costs of school supplies, transportation, and nutritional supplement, while the private school tuitions do not. Also, many private schools impose additional fees for school activities and expect parents to make "voluntary" donations (bonos). Unfortunately, the data base we are using for this study does not contain information on the tuitions and fees of individual private schools.

Increasing Access to School

In 1997, when the Penalosa mayoral administration came into office, it found more than 140,000 children in the city from the lowest income level out of school. Of those students from low income families who were in school, close to one third were enrolled in private unsubsidized schools of dubious quality (SED, 2000). With the firm commitment of guaranteeing access to publicly funded schooling to all school-aged children from the lower income groups, the Department of Education focused its efforts on expanding access and on targeting its resources to the neediest population. In order to accomplish this, it has increased class size[8], reassigned teachers from administrative posts to classrooms, and constructed or rehabilitated classrooms in run down schools.

As demand continues to surpass the public schools' capacity, DOE is increasingly relying on the private sector to provide schooling services to low income students. It accomplishes this in part by subsidizing selected private schools based on the number of low income students they enroll [9] With the above strategies, DOE has been able to open more than 300,000 new spaces in schools over the past six years.[10]

Growing pains?

[8] DOE established a minimum of 35 students per class in grades 1-5, and of 40 in grades 6-11

[9] Publicly funded school places are assigned preferentially to students from estrato 1 & 2. The identification of eligible students is based on the city's system of stratification of the place of residence (estrato1-6), and through SISBEN, a system that includes SES indicators such as average educational level of parents, number of economically dependent family members in the household, measures of crowdedness in the home, access to basic services, among others.

[10] Although we have no concession schools in our sample, eight of the private schools in our sample received subsidies in the years of this study. Five of the eight private schools receiving government subsidies were for-profit, two were religious schools, and the other was a cooperative school (This information was based on the DoE's 1999 School Directory (SED, 1999b)

Bogotá's remarkable success in reorganizing its educational system and in expanding its capacity has turned the city into a role model for other Colombian and Latin American cities (See Lowden, 2002; Villa & Duarte, 2002). Questions now arise as to the impact that the reforms aimed at increasing access have had on the quality of education provided to students.

One potential quality concern is that class sizes in public sector schools have risen markedly. A second is that schools may be becoming more segregated by socioeconomic status as students from the lowest income groups are given preferential assignment to public and private subsidized schools, leaving middle class children to attend unsubsidized private schools. A third is that as the city increases its subsidies program, private schools accustomed to serving a relatively affluent population are increasingly serving children from low income families. Serving well children who come to school without the advantages of their regular clientele may pose greater challenges for private schools. A fourth is that to keep costs down, private schools may increasingly exercise the option of hiring as teachers adults with little pedagogical training or teaching experience. If class size, peer groups, and teacher qualifications affect student achievement, the reforms aimed at increasing access may jeopardize quality. This study sheds some light on the effects that these factors have on student achievement.

III. Methods

To address our research questions, we designed a longitudinal multi-level study of 5th grade classrooms in public and private schools in Bogotá, Colombia. Students were tested and interviewed at the end of the 4th grade school year in October-November 1999, and one year later at the end of 5th grade. Information was also collected on the students' 5th grade Mathematics teacher.

Data Set

The panel data set that we created for this study contains information collected from students, teachers and school principals in a stratified random sample of public and private schools in Bogotá. For analytic purposes, the final sample used in this study contains information on all students for whom 5th grade mathematics test scores are available and who have matching information on their 5th grade mathematics teacher. The data set contains information on 3,095 students from 73 schools, grouped in 97 5th grade classrooms and taught by 77 mathematics teachers. Of these students, 1,660 (54%) were enrolled in private schools and 1,435 students (46%) in public schools.

A particular characteristic of this data set, which drives an important part of our analysis, is that of the 77 teachers in the sample, 13 taught fifth grade mathematics to multiple groups of children. As we discuss below, this characteristic of the data allows us to estimate the impacts of class size and peer group quality on student achievement, controlling for teacher effects.

In selecting the sample for this study, we stratified schools by sector (public & private) and by school socio-economic status (SES)[11] and then selected schools from these strata randomly. We collected information from all teachers and students in all the 4th and 5th grade classrooms in each of the selected schools. Figure 1 contains a flowchart that describes how we arrived at the final analytic sample. In 1999, out of the 102 schools selected for the study, 14 refused to participate. One year later, we contacted the 88 remaining schools for follow-up. On this occasion, 10 schools refused to participate, one school did not offer 5th grade, and in four schools the 5th grade Mathematics teacher did not answer the questionnaire. Of the 3,095 5th grade students tested in 2000, 714 were either "new" to the school or had been absent from school the previous year on the day the fourth grade tests were administered. For these students, we imputed a pretest score using a hotdecking procedure.[12] [13]

[11] For administrative purposes, Bogotá is stratified into 6 distinct socio-economic strata with 6 being the highest. Schools in Bogotá are highly segregated by socio-economic level.

[12] The personal and family characteristics used in this procedure included students age, gender, # of days absent from school, mother's education, mother head of household, family's ownership of an encyclopedia, computer, car, refrigerator, washing machine, vacuum cleaner, phone, and having access to electricity in the home. All of the latter have been used as indicators of the student's socio-economic level. We also fitted our final models on the smaller sample of students for whom we had complete data. The results were not substantively different from those reported in the paper.

[13] In order to evaluate the generalizability of our study's findings to the population from which our sample was drawn, we assessed whether the schools and students that did not respond in the second wave of data collection differed in any systematic manner from those that did. On average, non-matched students are more likely to be male, to have obtained lower scores on the tests, to come from single mother households and to have been absent from school more often. Although proportionally more public schools dropped out of the study than did private schools, we found no statistically significant differences in school average pre-test scores or school SES between public schools that participated both years and those that dropped out of the study after the first year. However, among private schools, those schools that participated in both years had, on average, higher pre-test scores and student SES than those schools that dropped out after the first year.

<<insert Figure 1 here>>

Measures

Our data analyses involve three types of variables (outcome variables, question predictors and control predictors) measured at four different levels of analysis (the student, the classroom, the teacher, and the school-level). Table 2 lists the variables and provides brief descriptions.

<< insert Table 2 here>>

Student-Level Outcome and Explanatory Variables

Table 3 presents the means and standard deviations of the variables included in our data-analysis for the full sample of students and separately for students in public schools and private schools. We discuss differences between the sectors later in this section.

<< insert Table 3 here>>

<u>Outcome Variable</u>

Our outcome variable is each student's score (MSCORE) on an IRT-scaled Mathematics test developed by UNESCO/OREALC (Laboratorio Latinoamericano de la Calidad-- LLECE)[14] and administered to students in the final weeks of their 5th grade school year. This test has two parallel forms (Form A and Form B), each containing 32 questions. We used both forms of this test in the study, randomly distributing each form to approximately half the students in each classroom.[15]

Regardless of test form, the average Mathematics score across all students in the sample was almost 300 points, with a standard deviation of about 40. The scores ranged from 171 for students who answered only 5 questions correctly on either form, to 461, the highest possible

[14] This test was developed in 1997 for an international comparative study of 3rd and 4th graders organized by UNESCO's Laboratorio Latinoamericano de la Calidad (LLECE). 13 Latin American countries, including Colombia, participated in this study. Curriculum and testing experts from all participating countries, with the help of ETS, developed and pilot tested the instruments to make them reflect the curriculum of the first four years of primary education of the participating countries.

[15] The reported Cronbach's alpha reliability for Form A of the test is .86 and for Form B is .88 (UNESCO, 1998, p.67).

score on Form B obtained by 6 students and to 492 on Form A, obtained by 5 students. Even though both forms of the test were IRT-scaled and nominally parallel, and therefore student mathematics scores should be equatable across test forms, we included as a control variable in the analyses a dichotomous predictor to distinguish the form of the test taken (A or B).

Student-level Control Predictors

We included as control variables the average of each student's scores on achievement tests in Mathematics and Language taken at the end of the fourth grade and the square of the average score.[16] In doing this, we assume that the pretest scores capture students' total educational experience up to that point in time, as well as the effects of other earlier student background factors that may be influencing their achievement.[17]

We included two student demographic characteristics as controls: (a) AGE, the student's chronological age, measured in years, and (b) FEMALE, student gender, measured as a dichotomous variable (coded 1 for female, and 0 for male).

Notice, in Table 3, that of the 3,095 students in the sample, 57% are girls. This is due to the inclusion of 19 all-female classes (and two all-male classes) in the sample of 99 classes. Also, boys were more likely to change schools and to be absent from school, preventing us from matching them on the two years of this study. Students in the sample are on average 10.8 years old, and their ages range from eight to seventeen.

We used two sets of variables as indicators of student SES: (a) MHH, a dichotomous indicator of whether the mother was head of the household (coded 0=no, 1=yes), and (b) indicators of the Mother's educational attainment.[18] Approximately one quarter of the students

[16] The 4th grade tests used in this study were developed by Universidad Nacional for Bogotá's Department of Education 1998 student assessment program where they were used to test 3rd graders.

[17] The pre-tests had 3 parallel forms, each containing 17 questions on Mathematics and 17 on Language. We administered all three forms of the pretest, randomly distributing the forms to approximately one third of the students in each classroom. Items were scored separately by subject specialty, on a scale ranging from 0 to 306. Students achieved an average of 200.3 points (st. dev. 50) with scores ranging from 12 to 306 points (6 students in the sample obtained perfect scores). There are no published reliability or validity estimates for the pretests.

[18] In our sample, 356 observations (9.9% of the student sample) were missing information on Mother's education. We imputed these missing values by substituting the median value for the student's classmates. Likewise, 178 observations (4.9% of the student sample) were missing data on whether their mother was head of the household (MHH). Given that we constructed this variable based on students' responses to whether their father lived with them or not, in the cases where they failed to answer we assumed that their father did not.

in the sample lived in mother-headed households. The median and the modal level of mother's education was some high school.

We also included as controls indicators of students' opportunity to learn, including school attendance, the availability of books in their home, and the support provided at home for the completion of homework. Previous studies in Bogotá have found these variables to be related to student achievement (Sarmiento, et al., 2001). We measured these variables, as follows:

- **DAYABS**, the numbers of days that the student was absent from school over the previous two weeks.[19]
- **HWHELP**, the frequency with which a student receives help with his or homework at home, measured with a Likert-type scale (where 1=never receives help, 2=sometimes receives help, 3=always receives help). In the data-analyses, we converted this ordinal variable into a system of dichotomous (dummy) predictors, with HWHELP3 (always receives help) being omitted from the fitted models as a reference category.[20]
- **BKS**, measuring the availability of reading books in the student's home, a composite standardized to mean of 0 and standard deviation of 1).[21]

In spite of the low levels of mother's education among students in the sample, 97% of students report having reading books in their homes and 93% report receiving help sometimes or always with their homework at home. Students in the sample were absent from school an average of 0.64 days in the two weeks preceding completion of the questionnaire.

Question Predictors

To answer our research questions on the influence of classrooms, teachers and peers on student achievement, we included two classroom-level question predictors and two teacher-level predictors in the data-analyses.

[19] In the 77 cases (2.8% of the student sample) in which information was missing on this variable, we substituted the sample mean for the missing value.

[20] In the 19 cases (0.7% of the student sample) in which information was missing for this variable, we substituted the value 2, which was the modal response.

[21] For the 15 cases (0.5% of the student sample) in which information was missing on this variable, we assumed that there were no books in the home.

Classroom Characteristics

The variable that we used to represent the effect of peer-group composition on student achievement is the “leave-out” mean (Boozer and Cacciola, 2001) of the student’s classmates’ mothers; educational level (CLMOTHED). This is defined as the classroom mean of mother’s education, leaving out each student’s own value from the calculation. As can be seen in Table 3, students in the sample are likely to have a peer-group whose average level of Mother’s education is an incomplete secondary school education. However, there is considerable variation across classrooms.

We measure class size as the number of students enrolled in each classroom as reported by the teacher. On average, classrooms in the sample have 37 students (std.dev. 8.5) although they range from having 10 to 53 students per class.[22] Based on exploratory analyses showing a non-linear relationship between class size and student achievement, we defined our class size variable as the natural log of the maximum class size (53) + 0.167 – class size, or ln[53.167-class size]. We followed Tukey’s advice in adding the value of 0.167 to the maximum class size.

Teacher Characteristics

We included two sets of characteristics of teachers that are rewarded by the existing salary structure. The first measures educational preparation to teach. The original ordinal variable indicates the teacher’s highest educational degree obtained (coded: 1= Pedagogical High school; 2= Education technology (2- or 3-year post secondary certificate); 3=Licensure in Education (A four year university level program); 4=Post graduate courses, including Masters in education (2 year + thesis), or specialization (1 or 2 years graduate level program); 5= graduate from a 5 year university-level program in a field other than education). In our analyses, we converted this ordinal variable into a system of dichotomous (dummy) predictors, with EDLEVEL3 (licensure) omitted from the fitted models as a reference category. In our sample, 49% of teachers have a four-year college degree in education (licensure), 38% have either a Master’s degree or a specialization or are currently enrolled in a program at this level, and only 7% have no formal training in education.

[22] Averaged over students rather than classrooms, the mean is 36 students.

We measure teacher experience (TEAEXP) by the number of years that the 5^{th} grade Mathematics teacher has been in the teaching profession. Given that previous research suggests that the relationship between student achievement and teachers' years of experience is non-linear (Rivkin, Hanushek, and Kain, 1998; Murnane & Phillips, 1981; Rockoff, 2003), we included the natural log transformation of this variable (L_TEAEXP) as a predictor in the regression analyses. On average, teachers in the sample have 16 years of teaching experience (std. dev. 9.8), while 11% have 3 years or less of experience.

School Sector

In order to examine the effect of school sector on student achievement, we included a dichotomous predictor (PUBLIC), coded Public=1, Private=0. Fifty four percent of the students in the sample attended private schools. A total of 59 private school classrooms located in 47 private schools are included in the sample. Thirty-seven of the private schools in the sample are for-profit schools, nine are run by religious organizations, and one is a cooperative school.

Data- Analytic Strategy

We hypothesized that the academic achievement of students with similar background characteristics will differ as a result of differences in the skills of their teachers, the quality of their peer groups, class size, and the institutional arrangements of their schools. These hypotheses imply that variability in student achievement may be partitioned into *within-classroom* variability that is attributable to differences among individual students, and *between-classroom* variability that can be attributed to differences among classrooms. Because we intend to determine those classroom composition and teacher-related characteristics that are responsible for the between-classroom variability in student achievement, we treat all other individual and school characteristics as control variables. Given that our data have a structure in which students are "grouped" within classrooms, which are grouped in turn within teachers or within schools, we have used multi-level modeling to conduct the analyses. Multilevel modeling enables us to decompose variation in the outcome into its *within-classroom* or *within- teacher* and *between-classroom* or *between-teacher* components, thus allowing for a more precise description of the relationship between the outcome and predictors measured at different levels of the educational structure (Bryk and Raudenbush, 1992).

Research Questions 1a & 1b

On average, do children enrolled in some 5th grade ***classrooms*** *in Bogotá have higher end-of-year mathematics achievement than children in other classrooms, controlling for student SES and end of 4th grade achievement?*

On average, do children assigned to some 5th grade mathematics ***teachers*** *in Bogotá have higher end-of-year mathematics achievement than children assigned to other teachers, controlling for student SES and end of 4th grade achievement?*

We address these "baseline" questions using a fixed effects regression analysis that models the relationship between a student's 5th grade mathematics achievement score and a set of dummy predictors representing CLASS membership (Model 1a) or TEACHER membership (Model 1b), controlling for a vector of student background characteristics. In these hypothesized models, we allow all students in each classroom or each teacher group to possess a unique shared intercept parameter. Inspection of estimates of these intercepts allows us to investigate whether classrooms or teachers differ in student achievement, net of background student characteristics. Moreover, any differences in "fit" between the teacher and classroom models suggests the existence of classroom effects on student achievement that are unique from those of the teacher, an issue that is the focus of further attention in this study. The hypothesized fixed-effects Models are as follows:[23]

(1a) $Y_{ij} = \beta_{0j} + \beta_1 S_{ij} + \varepsilon_{ij}$

(1b) $Y_{ik} = \beta_{0k} + \beta_1 S_{ik} + \varepsilon_{ik}$

Where:

$Y_{ij/k}$=5th grade Mathematics score of a student i in classroom j or with teacher k.

$\beta_{0j/k}$= the intercept for classroom j or teacher k, adjusted for a vector of student characteristics. (The population value of mathematics achievement for a student

[23] Alternatively, following Hanushek's (1971) notation, these Models can be expressed as follows: $Y_{ij} = \sum\beta_j CLASS_j + \beta_1 S_{ij} + \varepsilon_{ij}$ or $Y_{ij} = \sum\beta_k TEACHER_k + \beta_1 S_{ik} + \varepsilon_{ik}$ where CLASS and TEACHER represent the dummy variable for each teacher or class in the sample.

whose values on all student-level controls are equal to the respective grand mean). In the case of β_{0k}, the intercept is the weighted average intercept across all the classrooms taught by each particular teacher.

$S_{ij/k}$ = a vector of student characteristics for student i in classroom j or with teacher k, each variable centered on its respective grand mean, $\overline{X}_{\bullet\bullet}$.

β_1 =the effect of the personal characteristics of pupil i in classroom j or teacher k on student achievement

$\varepsilon_{ij/k}$= residual for pupil i in classroom j, or teacher k

In order to assess whether classrooms or teacher groups each have an identical impact on student learning net of individual student characteristics, we use a general linear hypothesis test to test the null hypothesis that all the fixed-effects classroom coefficients β_{0j} or teacher coefficients β_{0k} are simultaneously equal. If we reject these null hypotheses, we can conclude, in Model A, that the classroom in which the student spent the 5th grade made a difference to his or her end of 5th grade Mathematics achievement score; or, in the case of Model B, that the teacher/classroom combination that the student was assigned to made a difference to his or her end of 5th grade mathematics achievement score, net of student controls.

Second, in order to examine whether there are classroom-specific characteristics that exert an influence above and beyond the impact of the teacher, we use a general linear hypothesis test to test the null hypothesis that all classroom coefficients β_{0j} *for those groups of classrooms taught by the same teacher* are simultaneously equal. If we can reject the null hypotheses, we can conclude that even among classrooms taught by a same teacher, average student's achievement differs across classrooms, net of individual-level student controls.

While the above strategy is useful for detecting the presence of a classroom or teacher effect, net of variation in the student-level controls, it does not reveal which specific classroom and teacher characteristics are responsible for the effects. Our next research questions examine this issue.

Research question 2

*On average, controlling for students' socioeconomic and academic backgrounds and for differences among their teachers, do **the student-body composition** and **class size** of the classroom in which a student spent the 5th grade influence his or her 5th grade mathematics achievement score?*

To answer this question, we fit a taxonomy of multi-level models in which we added classroom characteristics as predictors to the baseline individual-level control model which contained the teacher fixed-effects. With this strategy, we group classrooms within teachers, but include classroom characteristics as predictors for each separate classroom in which a given teacher teaches, thereby allowing for predictor variation across classrooms "within" teachers. Typical regression models have the following form:

$$(2) \qquad Y_{ijk} = \beta_{0k} + \beta_1 S_{ijk} + \beta_2 C_{jk} + \varepsilon_{ijk}$$

Where:

Y_{ijk}= the achievement of student i in classroom j, with teacher k.

β_{0k}= the average mathematics achievement of students in classrooms j with teacher k , adjusted for a vector of student and classroom characteristics.

S_{ijk}= a vector of student background characteristics for students i in classrooms j, with teacher k.

β_1= the effect of a vector of student background characteristics of student i in classroom j, with teacher k .

C_{jk}=a vector of classroom and peer-group characteristics of class j, with teacher k.

β_2= a vector of impacts of classroom and peer-group characteristics on student achievement.

ε_{ijk}= residual for student i in classroom j with teacher k.

In Model 2, we hypothesize a complex error structure that contains three parts: (1) an idiosyncratic student-level residual E_{ijk} that represents all unobserved student-level effects and measurement error for each student i in classroom j with teacher k; (2) a teacher-level residual U_k

that is constant for students in all classrooms with teacher k that represents all unobserved teacher effects; (3) a classroom-level residual U_j constant for students in each separate classroom, representing all unobserved classroom-level effects for classroom j:

$$\varepsilon_{ijk} = E_{ijk} + U_k + U_j$$

As several authors have noted (McEwan, in press; Hoxby, 2002), assignment of students to schools or teachers is seldom random. Thus, estimates of β_2 may be affected by selection bias. In this particular case, the classroom predictors of interest are likely to be correlated with unobserved class, teacher, and or school-specific components U_j or U_k. Because our goal is to obtain unbiased estimates of β_2, in Model 2, we treat U_k as fixed, thus obtaining estimates of β_2 from the variation in classroom characteristics among the separate classrooms that have a common teacher. This strategy allows us to control for a potential source of bias derived from the non-random assignment of students to the different teachers in a given school while allowing us to disentangle peer-group effects from teacher effects.

This analytic strategy produces unbiased estimates of β_2 only if students are randomly assigned to different classes taught by the same teacher. To learn about assignment processes, we interviewed a teacher or administrator in each of the 14 schools in which individual teachers taught mathematics to more than one fifth grade class. Our respondents reported that in all but two cases, students were assigned to classes to obtain a mix of student backgrounds and abilities in each class and to roughly equalize class sizes. In two cases students with especially low or high skills were assigned to a particular class. We eliminated the students in these two classes from the analytic sample.

To assess whether we could plausibly argue that students taught by the same teacher were not assigned to classes on the basis of ability or socioeconomic status, we utilized a strategy proposed by McEwan. This involved creating "virtual" classrooms by randomly reassigning students from separate classrooms into "new" classrooms. We then compared the distribution of class size and peer group composition in the "virtual classrooms" with those in the actual classrooms. We found almost no differences in the two distributions. Of course, a troubling consequence of this is that there is only very modest variation in class size and peer group composition among classrooms taught by the same teacher. As a result we have little variation to use in estimating the impact of these variables on student achievement.

Research Questions 3a, 3b, and 3c:

Controlling for student background characteristic, do students enrolled in private schools have higher student achievement than students enrolled in public schools?

Controlling for student background characteristic and peer group composition, do students enrolled in private schools have higher student achievement than students enrolled in public schools?

Controlling for student background characteristics, peer group composition, and class size, do students enrolled in private schools have higher student achievement than students enrolled in public schools?

To address question 3a we fit a model which is similar to model 1a, except that the classroom-specific intercepts are replaced by a common intercept and a dichotomous indicator (PRIVATE) that takes on a value of 1 if a student spent the fifth grade year in a private school classroom, and zero if the child spent the year in a public school classroom.

In address question 3b, we add peer group composition to the model described just above, constraining its coefficient to have the value estimated from fitting model 2.

To address question 3c, we add class size, also constraining its coefficient to have the value estimated from fitting model 2. The logic to constraining these coefficients to their model 2 values is that this model takes into account teacher quality differences with which class size and teacher quality may be correlated. The model for addressing question 3c has the following specification:

$$(3) \qquad Y_{ijk} = \beta_0 + \beta_1 S_{ijk} + \beta_2 C_{jk} + \beta_3 PRIVATE_{jk} + U_j + \varepsilon_{ijk}$$

Where:

β_3= the effect of the school sector of classroom j with teacher k, on student 5th grade mathematics achievement, controlling for all other predictors in the model

Notice that the hypothesized multilevel error structure retains its two components, but in this analysis, we treat the U_j as random effects, so that the outcome variation they represent can be explained by the school-level predictor introduced into the structural part of the model. If we can reject the null hypothesis that $\beta_3=0$, we will know that school sector predicts students' 5th grade Math achievement, controlling for vectors of classroom and students' background characteristics and for students' 4th grade achievement.

Research Question 4:

All else being equal, does a student's Math achievement at the end of 5th grade depend on his or her 5th grade Math teacher's qualifications and years of teaching experience?

To address this research question, we add predictors representing teacher experience and educational attainments to the hypothesized model. We fit a random effects model of the following type:

$$(4) \qquad Y_{ijk}= \beta_0 + \beta_1 S_{ijk} + \beta_2 C_{jk} + \beta_3 PUBLIC_{jk} + \beta_4 TEACHER_{jk} + U_j + \varepsilon_{ijk}$$

Where:

β_4= the effect of a vector of teacher qualifications and experience on students' 5th grade Math achievement, controlling for students'4th grade Math and Language achievement and for vectors of student, classroom and school characteristics.

Again, we constrain the coefficients on class size and peer group quality to the values estimated from fitting model 2. If we can reject the null hypothesis that $\beta_4=0$, we will know that the measures of teacher experience and educational qualifications predict students' 5th grade Math achievement controlling for vectors of students, classrooms and school characteristics.

III. Findings

Do Classrooms Matter to Student Mathematics Achievement?

Table 4 contains fitted fixed-effects regression models in which students' 5^{th} grade mathematics scores are predicted by systems of dummy variables distinguishing classrooms (Model A) and teachers (Model B), controlling for students' individual academic and background characteristics. As can be seen from the results of the tests of the equality of the fixed-effects across the 97 classrooms in Model A and across the 77 teachers in Model B, we can reject the null hypotheses that there are no differences among classrooms (p<.0001) nor among teachers (p<.0001). In other words, all else being equal, the 5^{th} grade classroom or teacher to which a student was assigned for the school year makes a difference to his or her end of 5^{th} grade mathematics achievement test.

<<insert Table 4 here>>

Figure 2, which presents a graphical representation of the distribution of the classroom-specific intercepts from Model 1A in Table 4, illustrates the magnitude of the differences in average mathematics achievement scores across classrooms, net of the effect of the control predictors. Ignoring the extremes of this sample distribution, which as Kane and Staiger (2001) suggest could be the result of measurement error or extraneous conditions, the overall size of this effect can be assessed by examining the inter-quartile range statistic, which is 17 points. This is approximately equal to the 18 point difference between the median score of 3^{rd} graders and that of 4^{th} graders when the same test was administered to large samples of students in these grades in Colombia in 1999 (Unesco/Orealc, 2000, p.258).

<<Insert Figure 2 here>>

Before turning to the roles of specific classroom factors in predicting student achievement, we summarize briefly the impacts of those student-level characteristics that have the strongest impacts on student achievement within-classrooms. First, as many other studies have shown, a student's achievement score at the end of one grade (4^{th}) is a strong predictor of the students' achievement at the end of the next grade (5^{th}). Second, on average, boys outperform girls by an average of 8 points (p<.0001). Third, younger students perform slightly better on average than older students (p<.001), probably as a result of accumulated academic failure among the latter. Fourth, 5th grade mathematics achievement also depends upon school attendance. Each day the student was absent in the two weeks before the math test was administered is associated with a decline of 1.8 points in test score ($p<.001$).

Is it the Teachers or the Classrooms that matter?

The evidence on the importance of classrooms in predicting student mathematics achievement raises question: *Do children in different classrooms taught by the same teacher differ from each other in 5th grade average mathematics achievement?* To answer this question, we tested for the equality of the classroom fixed-effects among groups of separate classrooms taught by the same teacher. Table 5 contains regression coefficients associated with the classroom fixed-effects for the 13 groups of classrooms in our sample that have a common mathematics teacher, and the results of the corresponding general linear hypothesis tests.

<< insert Table 5 here>>

For nine of the teachers who taught multiple classes, there are no statistically significant differences in the average net achievement of the students in different classes. On the other hand, for four of the teachers who taught multiple classes (indicated by the shaded rows in Table 5), there are quite large and statistically significant differences in the average net achievement of children in their different classes.

Do peer-group composition and class size matter to student mathematics achievement?

As other researchers have pointed out (Hoxby, 2000; McEwan, 2001; Boozer and Cacciola, 2001), the estimation of peer effects in classrooms has often been biased as a result of the non-random assignment of students to classrooms. To minimize this problem, we rely on variation in peer groups among classes taught by the same teacher in the same school.[24]

[24] Our estimation strategy requires variation in peer group characteristics across classes taught by the same teacher. Such variation raises the possibility that students could have been assigned to different classes taught by the same teacher on the basis of unobserved attributes that affect student achievement. This would create bias in our estimation of peer group effects. While we cannot totally discount this possibility, we were gratified to learn that the variation in average peer group characteristics among classes taught by the same teacher was only marginally greater than the variation that would have been present if students in particular schools were randomly assigned to classrooms (see McEwan, in press, for a discussion of this procedure.)

Models 2a, 2b, and 2c in Table 6 contain the estimated parameters of models that contain fixed effects for teachers and different combinations of the two class-specific variables, class size and peer group composition. As indicated in Models 2b and 2c, the point estimates suggest that students in classrooms in which their peers have more educated mothers achieve higher mathematics scores. While the relevant coefficients in the teacher fixed effects models are not statistically significant, they are similar in value to the statistically significant coefficients in the analogous models fitted with fixed effects. As other researchers have pointed out (e.g., Hoxby, 2000), peer-effects likely embody multiple mechanisms, including student-student interactions and teacher and/or administrator expectations.

As indicated in Models 2a and 2c, the class size indicator is a statistically significant predictor of student achievement. Figure 3, which is based on Model 2c, illustrates this relationship. Students in a class with 34 students (the private sector mean) are predicted to score 9 points higher (0.23 s.d.) than students in a class with 40 students (the public sector mean).

<< insert Table 6 here>>

<< insert Figure 3 here>>

If students were randomly assigned to teachers, we would expect no systematic relationship between teacher quality and either class size or peer group composition. However, if relatively effective teachers are assigned to the largest classes or to work with the most needy students, or if the reverseis true, then estimates of the effectiveness of individual teachers will be sensitive to whether the effects of peer group composition and class size are taken into account. Figure 4 illustrates the importance of taking class sizes and peer groups into account in estimating the impact of teachers on student achievement. Column 1 presents the ranking of the teacher-specific intercepts in the baseline control model (model 1b, Table 4). Columns 2 and 3 re-rank the teachers by their coefficients in the model that controls for peer group characteristics (model 2b, Table 6) and in the model that controls for both peer group composition and class size (model 2c, Table 6). The arrows between the columns show the changes in the quality rankings of teachers as estimated in models with different sets of classroom controls.

<< insert Figure 4 here>>

Notice the many changes in the relative quality rankings of specific teachers. For example, Teacher 72 ranked 43rd when only the student level controls were taken into account; then ranked 10th when peer-group composition of the class was included as a predictor and then ranked 1st with the inclusion of both peer-group composition and class size as predictors. This finding raises serious questions about school accountability initiatives that attribute differences in average student achievement across classrooms solely to differences in teacher quality.

Figure 5 presents box-plots representing the distribution of the coefficients on the teacher fixed-effects in Models 1b (Table 4) and in models 2b and 2c from Table 6. Notice that the variation in estimated teacher quality is much larger in Model 2c that controls for class size than in the models that do not. The explanation is that the more effective teachers are assigned to the largest classes in the data set. The net result is that differences in class size, when not taken into account, reduce the estimated variation in teacher quality. Figure 6, which plots the teacher-specific intercepts from Model 2c in Table 6 against each teacher's average class size, illustrates this pattern: the most effective teachers are assigned to the largest classes. This pattern explains why class size does not appear to be related to student achievement when estimated in the random effects model (2c (r.e.)) in Table 6) that does not control for teacher quality.

<< insert Figure 5 and Figure 6 here>>

Does School Sector Matter to Student Achievement?

Students in private schools in Bogotá have higher achievement scores, on average, than their peers in public schools. This is not surprising since private schools have higher concentrations of students with parents who have significant educational attainments and who can afford to pay school fees and purchase the required school supplies. The differences in the average background characteristics of public and private school students are indicated in Table 3. Public school students are less likely to live in mother-headed families than are private school students. Their mothers have more education, on average, than have the mothers of public school students. The differences in individual student characteristics between public and private schools naturally result in corresponding differences in the characteristics of peer-groups by sector. As a result, public school students have less advantaged peer groups than do private school students. Public school students are also likely to study in classrooms with larger class sizes than are private school students.

One respect in which public school students could have a potential advantage over students in private schools is in the academic preparation and experience of their teachers. No public school teachers in the sample have less than six years of teaching experience in contrast to 28% of private school teachers. While almost 70 percent of public school teachers have a Master's Degree or are working towards one, the corresponding figure for private school teaches is 16 percent. As explained above, this pattern stems primarily from the public school teacher salary scale and its applicability to private schools. The salary schedule provides strong incentives for public school teachers to gain educational credentials and to remain in teaching. The requirement that private schools pay teachers according to this same schedule creates incentives for private schools to avoid highly experienced teachers with significant educational credentials because they are very expensive. The two panels of Figure 7 illustrate the differences in the distributions of public school teachers and private school teachers on the common salary schedule. One-third of private school teachers are on the first step of the salary scale. No public school teachers are on the first step and more than 95% are on the top half of the scale.

<<Insert Figure 7 here>>

We turn now to the question of whether the differences in peer groups, class sizes, and teacher characteristics contribute to differences in the achievement of students attending schools in the two sectors. The regression results are displayed in Table 7, and are illustrated in the panels of Table 8. Panel A displays the distribution of average classroom-specific fifth grade math scores among classrooms in public schools and private schools in the sample. The mean of the distribution for students in private schools is 8 points higher than the mean for students of public schools. What is striking is the wide variation in classroom-specific average achievement among classes in both sectors. This highlights that private schools in the sample do not all serve high achieving students.

Panel B of Figure 8 displays the distribution of teacher-specific intercepts by sector from Model 3b in Table 7, which controls for student background characteristics including pre-score. The average achievement of students in the two sectors is not statistically different. However, there is substantial variation in the net average achievement of students in different classrooms in each sector.

Panel C of Figure 8 displays the distribution of teacher-specific intercepts by sector from Model 3c of Table 7, which controls for peer group as well as for student backgrounds. The coefficient on peer group in this model is constrained to its value in Model 2b of Table 6, a model that includes fixed effects for teachers. Net of these factors, the mean achievement of students in private school classes is four points lower than that for students in the public sector. This highlights that a high SES peer group is one of the relative advantages private schools have to offer, on average. However, again it is striking how great the variation in average student achievement is among students enrolled in the classes of different private school teachers.

Finally, Panel D of Figure 8 displays the distribution of teacher-specific intercepts by sector from Model 3d of Table 8, which controls for class size as well as for peer group and student background characteristics. The mean of the distribution of teacher-specific intercepts in the private sector is 14.5 points lower than the analogous public sector mean. The explanation is that class size and peer groups matter to student achievement and, on average, class sizes are smaller and peer groups are more advantaged in the private sector. Interpreting the teacher-specific coefficients in Panel D as our best estimates of teacher quality, the wide range of quality estimates for private school teachers is remarkable, especially relative to the magnitude of the variation in estimated effectiveness among public school teachers. The best private school teachers appear to be better than the best public school teachers while the worst private school teachers are considerably less effective than the worst public school teachers. Unfortunately we do not know whether the least effective private school teachers are more likely to be dismissed for poor performance than the weakest public school teachers are.

<<insert Table 7 here>>

<< insert Figure 8 here>>

Do Teacher Qualifications and Experience matter to Student Achievement?

The difference between the two sectors in the average quality of teachers and the extraordinary variation in teacher quality among teachers in the private sector prompts the question: do experience and educational credentials, the attributes rewarded in the national teachers contract, predict teaching performance?

To answer this question, we fit a taxonomy of regression models presented in Table 8 that estimate the effects of teacher education and years of experience on student mathematics achievement, with classrooms treated as a random effect. In estimating Models 4a and 4b we constrain the coefficients on the peer group measure and the class size measure to the values estimated in the fixed effects analysis (Model 3c, Table 6). The reason is that these variables are correlated with teacher quality and the random effects models do not control completely for teacher quality. For comparative purposes, we refit these same models with these coefficients left unconstrained (Models 4c and 4d).

<<insert Table 8 here>>

Figure 9 illustrates the fitted relationship between teacher experience and student achievement from Model 4b in Table 8 (which does not control for sector). Notice that there is an initial rapid growth in teacher effectiveness during the teachers' first years in the classroom after which the effect of experience grows at an increasingly slower rate. This finding supports the hypothesis that the greatest gains from additional experience occur during the first years of teaching.[25] Notice, however, that in Models 4c and 4d the coefficient on this predictor is close to zero, suggesting that more experienced teachers appear to be assigned to larger classes and the most needy groups of students, thus exerting a compensatory effect that neutralizes the effects of experience.

<< insert Figure 9 here>>

Notice in Models 4a and 4b that teachers who have less than a four year college education are less effective, on average, than those with a four year degree. Nine percent of the

[25] Other studies that show this same pattern include Rivkin, Hanushek and Kain, and (1998), Murnane and Phillips (1981), and Rockoff (2002).

teachers in private schools in the sample have less than a four-year degree compared to two percent of public school teachers. Thus, differences in educational credentials and years of teaching experience help to explain the difference between the average quality of private school teachers and those of public school teachers.

It is also important to point out the fitted models 4a and 4b indicate that teachers with educational credentials beyond a four-year degree (EDLEVEL4) are not more effective, on average, than are those with a four-year degree. This supports the view of many Bogota school officials that a salary schedule that rewards post-graduate educational credentials is not an efficient use of scarce resources.

A final pattern to notice is that the percentage of the variation in student achievement explained by Model 4b of Table 8 (20.6), a random effects model that measures teacher quality by experience and educational credentials, is much lower than the percentage of variation explained by Model M3 of Table 6 (36.9), a model which includes fixed effects for teachers. One way to interpret this evidence is as follows. Information about educational credentials and years of teaching experience are useful in predicting teacher quality. However, they explain only a small part of the variation in effectiveness among teachers in enhancing student achievement.

IV. Lessons

This study supports a pattern reported in many other studies: students learn markedly more over a school year in some classrooms than they do in others at the same grade level. We show that differences in class size, in peer groups, and in the quality of teachers all contribute to differences in learning across classrooms. Furthermore, we show that in this sample the most effective teachers tended to be assigned to work with the largest classes and the most needy groups of students. Not taking this into account in evaluating the effectiveness of teachers results in underestimating the effectiveness of the best teachers and overestimating the effectiveness of the weakest teachers.

On average, we find no difference between the average achievement of students attending public schools and private schools, net of family background and prior achievement. However, there is enormous variation in the average net achievement of students enrolled in different classrooms in each sector, with the variation across classrooms especially large in the private sector. As a result, the important choice for a parent is selecting a school and a class within a sector; not which sector to choose to enroll one's child in. At the same time, there are striking differences in the average characteristics of public schools and private schools in the sample. Classrooms in private schools tend to have smaller classes than those in public schools and more advantaged student peer groups. However, teachers in private schools tend to have less teaching experience and less educational preparation. All of these differences contribute to differences in student achievement.

In evaluating the evidence on public school-private school comparisons, it is important to keep in mind the rules under which the private schools in this sample operate. Private schools in Bogotá are constrained to pay teachers according to the public school teachers' salary schedule that bases pay on educational credentials and years of teaching experience. They were also constrained in the rate at which they could increase tuition. Our study provides no evidence about whether the relative effectiveness of public schools and private schools would have been different had the rules governing these schools been different.

We find that years of teaching experience is positively related to teaching effectiveness, but in a non-linear way. The greatest improvement in effectiveness take place during the first years in the classroom. We also show that educational credentials predict teaching effectiveness. The strongest evidence is that, on average, teachers who have less than a four-year college degree are less effective than those who have at least this much education. Given that most private schools are under pressure to meet costs and that the salary schedule makes it expensive to hire experienced teachers with four year college degrees, it is not surprising that the percentage of teachers with little experience and with less than a four-year college degree is much higher in the private schools in our sample than in the public schools.

While teaching experience and educational credentials are positively related to student achievement, they explain only a small portion of the differences among teachers in predicted effectiveness. This pattern provides support for those who argue that a salary schedule that bases teacher pay solely on experience and educational credentials may not be an efficient way to use scarce resources.

Finally, the importance of peer groups in influencing student achievement creates a difficult public policy problem. It creates strong incentives for parents with resources to try to place their children in schools with advantaged peers and for schools interested in attracting students from such families to specialize in serving such families. The resulting sorting by socioeconomic status widens inequality in access to good schooling. As Hoxby (2001) has shown, differentially valued subsidies can contribute to a solution to this problem. However, it remains to be seen whether this can take place in a city in which the primary goal has been to increase access to schooling for the burgeoning student population.

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Table 1
Colombia's Teacher Salary Schedule for Teachers who entered the Profession before June, 2002
(Law 2277, 1979; Decree 259, 1981)

Academic Title	**Entering Step:**	**MAX**	**Years of experience required to move one step: 3 years EXCEPT:**			**Certified courses are required to move from one step to the next for the following:**	**Step**	**2003 Monthly Salary[26] in Colombian Pesos[27 28]**
Pedagogical High School (6 years of high school)	1	8	From step 1 to step 2: 2 years	From step 6 to step 7: 4 years		Step 2 -3 Step 4 -5 Step 6 -7	1 2	467,750 484,853
"Specialist" in Education (1 year post secondary)	2	8	From step 4 to step 5: 4 years	From step 7 to step 8: 4 years		Step 3-4 Step 5-6 Step 7-8	3 4	514,523 534,835
"Expert" in Education (2 years post secondary)	4	10	From step 6 to step 7: 4 years	From step 9 to step 10: 4 years		Step 5-6 Step7-8 Step 9-10	5 6	568,569 601,429
Technician in Education (3 years post secondary)	5	11	From step 7 to step 8: 4 years	From step 10 to step 11: 4 years		Step 6-7 Step 8-9 Step 10-11	7 8	683,480 752,391
Profession other than Education (5 years post secondary)	6 (after entry course)	14	From step 8 to step 9: 4 years	From step 11 to step 12: 4 years	From step 13 to step 14: 2 years	Step 7-8 Step 9-10 Step 11-12	9 10	834,992 915,290
Licensure in Education (4 years post secondary)	7	14	From step 11 to step 12: 4 years	From step 13 to step 14: 2 years		Step 8-9 Step 10-11 Step 12-13 Step 13–14: Graduate degree or publication	11 12 13 14	1,047,409 1,250,450 1,388,892 1,586,175

Notes:
1. Teachers obtaining an academic title other than the one with which he/she entered the salary scale moves up automatically to the corresponding entering step for that academic level.
2. Teachers working under "difficult" conditions as established by the Ministry of Education (rural areas, one teacher school) get double time.
3. Each publication gives teachers a two-year bonus.

[26] The benefits factor is 1.45 (not incuded) (SED,2003)
[27] Source: SED.(Decreto Nacional de Salarios, No.688, Abril 2002)
[28] Exchange rate in January 2003: US$1 = approx.3,000 Colombian pesos

Figure 1
Sampling Process for the Two-Wave
Data Collection

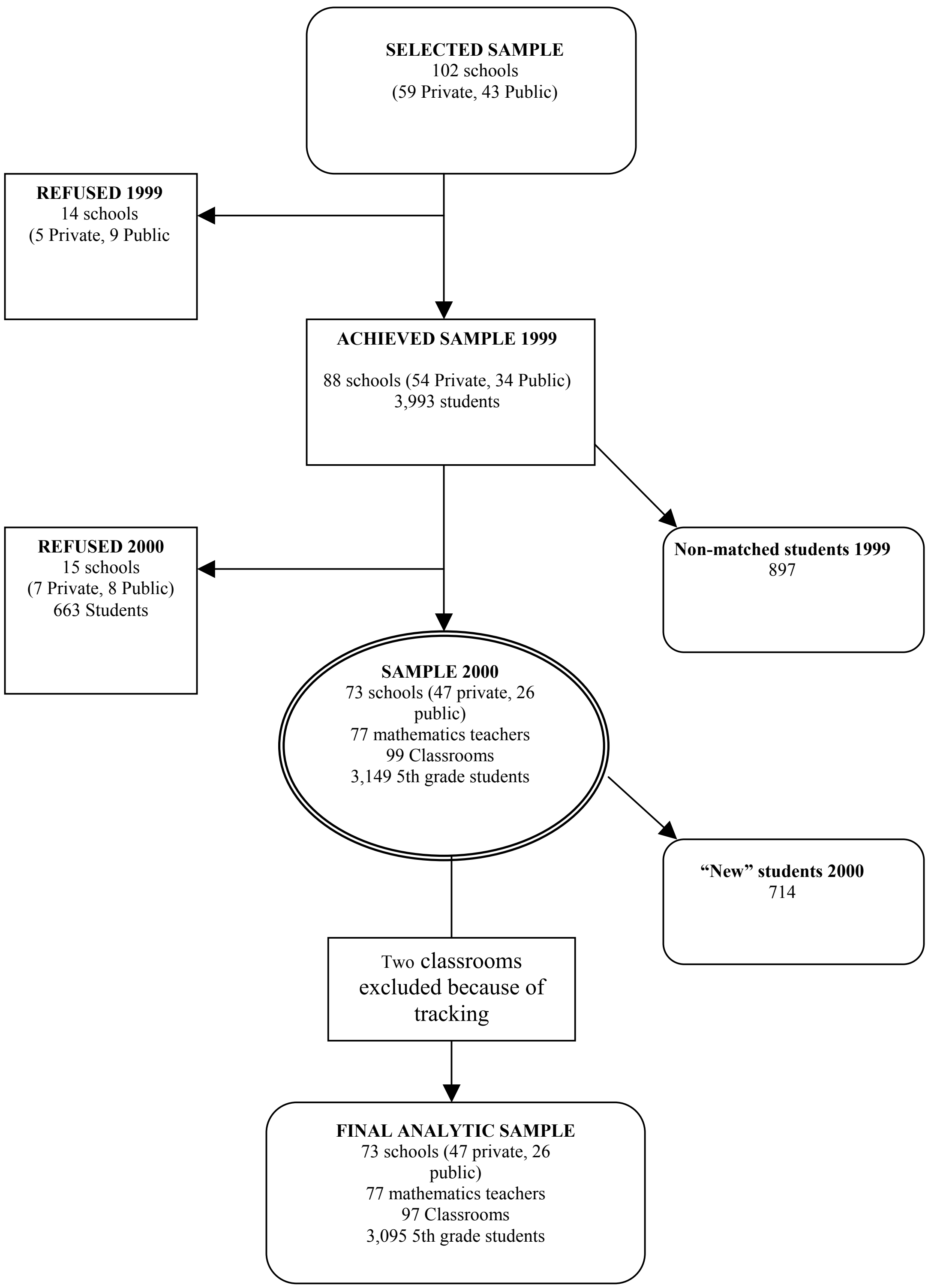


Table 2
Description of Outcome, Predictor and Control Variables

VARIABLE	DEFINITION
OUTCOME VARIABLE	
MSCORE	Mathematics achievement score in a standardized test administered at the end of 5^{th} grade scored from 0-492 points
STUDENT-LEVEL CONTROL VARIABLES	
FORM	A dichotomous variable indicating for of the test taken (0= Form B, 1=Form A)
PRETEST	Achievement score in a mathematics and language test administered at the end of 4^{th} grade, scored from 0-306 points.
AGE	Student's age at the end of the 5^{th} grade school year measured in years.
FEMALE	A dichotomous variable indicating student's gender (0=Male, 1=Female)
MOTHED	An ordinal variable indicating Mother's educational level where 0=no education, 1=incomplete primary, 2=complete primary, 3=incomplete secondary and, 4=complete secondary and beyond.
MHH	A dichotomous variable indicating whether the student's mother is the head of the household (0=No,1=Yes)
DAYABS	# of days that the student was absent from school in the last 2 weeks.
HWHELP	A system of dummy variables that measure the frequency with which the student receives help with homework at home (1=never, 2=sometimes, 3=always). HWHELP3 (always receives help) acts as the reference category.
BOOKS	A factor composite measure estimated with PCA of the availability of books, story-books and encyclopedia in a student's home. It is a standardized variable with positive scores indicating better availability (mean=0, SD=1).
CLASSROOM PEER-GROUP COMPOSITION and CLASS SIZE	
CLMOTHED	"Leave-out" classroom average level of students' mother's education.
CLMEAN	"Leave-out" classroom mean score on the pretest
CLASSIZE	A continuous variable indicating number of students enrolled in the classroom
TEACHER CHARACTERISTICS	
EDLEVEL	An ordinal variable indicating teacher's maximum educational level obtained or in process of obtaining. We converted this variable into a system of dichotomous (dummy) predictors, in which EDLEVEL1= Pedagogical high school; EDLEVEL2= Educational Technology; EDLEVEL3=Licensure in education; EDLEVEL4= Post graduate courses including Master's degree or specialization in education, and EDLEVEL5=other profession. EDLEVEL3 (licensure) was omitted from the fitted models as a reference category.
TEAEXP	Continuous variable indicating total number of years that the teacher has been in the teaching profession.
SSCALE	Ordinal variable indicating the step in the salary scale (1-14)
SCHOOL CHARACTERISTICS	
PRIVATE	Dichotomous variable indicating whether the school is public or private (1=Private, 0=Public)

Table 3
Descriptive Statistics of Outcome and Control Variables, by Sector

VARIABLE	FULL SAMPLE n students =3,095 n classrooms=97 n teachers=77 n schools=73	PUBLIC n students=1,435 n classrooms=38 n teachers=29 n schools=26	PRIVATE n students=1,660 n classrooms=59 n teachers=48 n schools=47
OUTCOME VARIABLE			
MSCORE	297.6	292.3	302.2
	(39.1)	(38.1)	(39.4)
STUDENT-LEVEL CONTROL PREDICTORS			
PRETEST	200.2	191.2	207.9
	(50.1)	(49.4)	(49.4)
FEMALE	.57	.59	.56
AGE	10.8	11.0	10.7
	(.97)	(1.1)	(.83)
DAYABS	.65	.73	.58
	(1.4)	(1.5)	(1.3)
MHH	.25	.27	.22
MOTHED1	.06	.09	.04
MOTHED2	.26	.32	.20
MOTHED3	.37	.40	.35
MOTHED4	.31	.19	.41
BOOKS	0	-.16	.14
	(1.00)	(1.16)	(.81)
HWHELP1	.07	.07	.07
HWHELP2	.81	.8	.82
HWHELP3	.12	.13	.11
CLASS-LEVEL PREDICTORS			
CLMOTHED	2.9	2.7	3.1
	(.48)	(.37)	(.47)
CLMEAN	200.2	191.2	207.9
	(25.6)	(22.9)	(25.3)
CLASS SIZE	36.8	40.2	33.9
	(8.5)	(3.8)	(10.1)
TEACHER PREDICTORS			
EDLEVEL1	.05	.02	.07
EDLEVEL2	.01	0	.02
EDLEVEL3	.49	.30	.65
EDLEVEL4	.38	.68	.12
EDLEVEL5	.07	0	.13
TEAEXP	16.2	19.9	12.9
	(9.8)	(7.7)	(10.1)
SSCALE	8.3	11.1	5.9
	(4.3)	(2.4)	(4.2)

Table 4
Regression of 5th Grade Student Mathematics Achievement Scores on Controls and Classroom and Teacher Fixed-Effects
(n students=3,095; n classrooms=97; n teachers=77)

CLASSROOM FIXED-EFFECTS Model 1a		TEACHER FIXED-EFFECTS Model 1b	
Predictor	**Coefficient**	**Predictor**	**Coefficient**
STUDENT-LEVEL CONTROL PREDICTORS			
FORM	-6.28***	FORM	-6.33***
PRETEST	0.308***	PRETEST	0.301***
PRETEST SQ	0.001***	PRETEST SQ	0.001***
FEMALE	-8.17***	FEMALE	-8.18***
AGE	-2.73***	AGE	-2.64***
AGE SQ	-0.84*	AGE SQ	-0.896**
DAYABS	-1.85***	DAYABS	-1.76***
MHH	4.63***	MHH	4.37***
BOOKS	2.39***	BOOKS	2.48***
HWHELP1	7.73**	HWHELP1	7.73**
HWHELP2	7.60***	HWHELP2	7.64***
MOTHED	0.512	MOTHED	0.606
Goodness of Fit			
R^2 "within"	0.201		0.196
R^2 "overall"	0.284		0.284
Test of equality of CLASS coefficients	$F_{96,2986}$=4.30***	Test of equality of TEACHER coefficients	$F_{76,3006}$=4.77***

~p<.10; *p<.05; **p<.01; ***p<.001

Figure 2
Adjusted Classroom Average Mathematics Achievement across 5th Grade Classrooms, Net of the Effect of the Control Predictors (based on Model 1a55 in Table 4)
(n students=3,095; n classrooms=97)

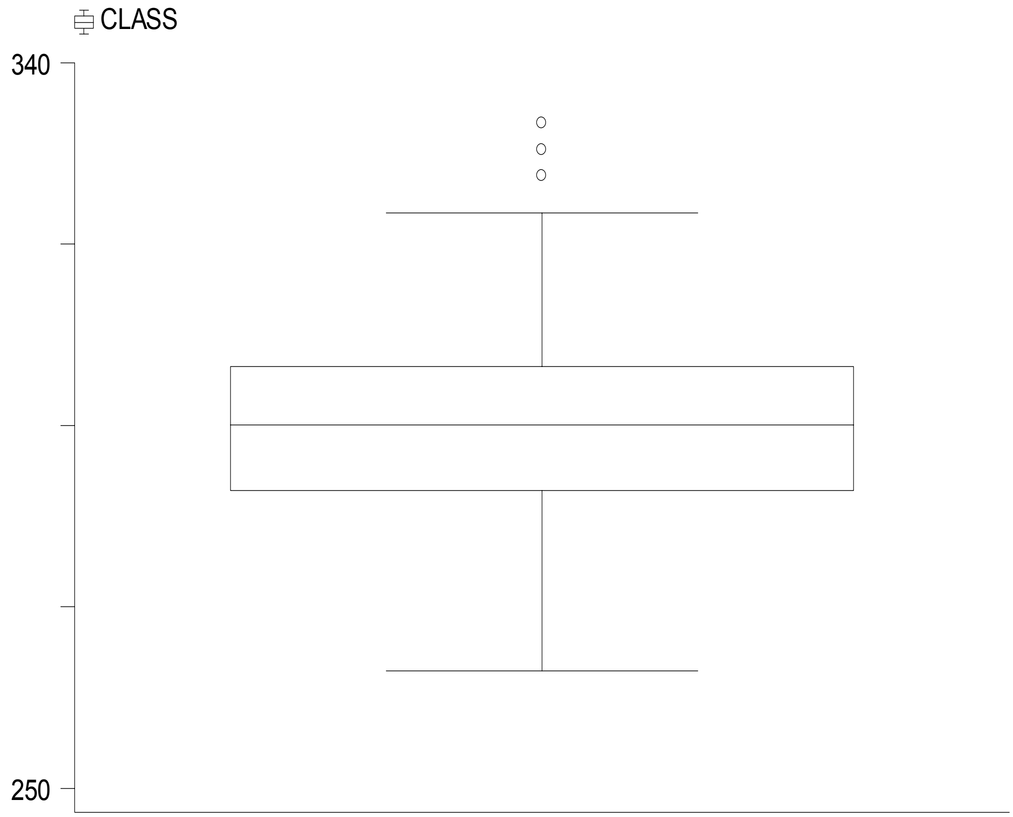


Table 5
Adjusted Classroom-Average Mathematics Achievement,
Net of the Control Predictors, by Teacher and Classroom

Teacher	Class 5-01	Class 5-02	Class 5-03	Class 5-04	F	P	Public
6	**Class # 6** 314.4	**Class # 7** 297.8			2.76	0.10	0
7	**Class # 8** 296.5	**Class # 9** 286.3			1.96	0.16	1
9	**Class # 11** 332.5	**Class # 12** 329.1			0.23	0.63	0
18	**Class # 21** 301.2	**Class # 22** 310.3			1.48	0.22	0
19	**Class # 23** 318.4	**Class # 24** 325.9	**Class # 25** 300.2		**6.03**	**0.002**	0
27	**Class # 34** 292.4	**Class # 35** 292.0			0.00	0.97	0
34	**Class # 43** 315.0	**Class # 44** 298.8	**Class # 45** 309.8	**Class # 46** 296.4	**3.22**	**0.02**	1
35	**Class # 47** 300.4	**Class # 48** 309.7	**Class # 49** 294.8	**Class # 50** 290.7	**2.72**	**0.04**	1
36	**Class # 51** 296.7	**Class # 52** 305.3			1.47	0.23	1
38	**Class # 54** 287.0	**Class # 55** 283.6			0.17	0.68	0
44	**Class # 61** 296.0	**Class # 62** 309.4	**Class # 63** 301.4	**Class # 64** 301.2	1.37	0.25	0
59	**Class # 79** 280.0	**Class # 80** 264.6			**4.69**	**0.03**	1
76	**Class # 97** 287.7	**Class # 98** 286.1			0.07	0.80	0

Table 6
Fixed and Random Effects Regression Models Estimating the Effects of Peer-Group Composition and Class Size on Students' 5th grade Mathematics Achievement Score
(n students=3,095; n classrooms =97; n teachers=77)

	TEACHER FIXED-EFFECTS			**CLASSROOM RANDOM-EFFECTS**		
	2a	**2b**	**2c**	**2a (r.e.)**	**2b (r.e.)**	**2c (r.e.)**
CONSTANT				296.027***	295.945***	296.091***
STUDENT-LEVEL CONTROL PREDICTORS						
FORM	-6.328***	-6.335***	-6.334***	-6.440***	-6.403***	-6.457***
PRETEST	0.302***	0.302***	0.303***	0.329***	0.314***	0.310***
PRETEST SQ	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
FEMALE	-8.160***	-8.145***	-8.140***	-7.358***	-8.125***	-8.160***
AGE	-2.579***	-2.649***	-2.593***	-2.160**	-2.311**	-2.214**
AGE SQ	-0.906**	-0.885**	-0.897**	-1.003**	-0.840*	-0.869*
DAYABS	-1.807***	-1.762***	-1.805***	-1.939***	-1.888***	-1.832***
MHH	4.385***	4.395***	4.399***	4.521***	4.730***	4.702***
BOOKS	2.453***	2.465***	2.446***	2.693***	2.363***	2.404***
HWHELP1	7.792**	7.672**	7.745**	7.650**	7.695**	7.626**
HWHELP2	7.592***	7.528***	7.526***	7.374***	7.503***	7.463***
MOTHED	0.579	0.936	0.796	1.868**	0.991	0.974
CLASS-LEVEL PREDICTORS						
CLMOTHED		**12.199**	7.932		13.805***	12.698***
CLASSIZE [29]	**26.534***		**23.919~**	**-0.483**		**-1.011**
Goodness of Fit						
R^2 "within"	0.198	0.197	0.198	0.200	0.201	0.169
R^2 "between"				0.660	0.664	0.638
R^2 "overall"	0.134	0.311	0.169	0.290	0.312	0.312
Teacher fixed effects?	yes	yes	yes	No	No	No

~p<.10; *p<.05; **p<.01; ***p<.001

(coefficients associated with the teacher fixed-effects have been omitted from the table)

[29] We have included here a modified log transformation of class size. In this transformation smaller values of class size correspond to larger values in the transformation (see description in Chapter 3).

Figure 3
Prototypical Plot Displaying the Relationship between Students' 5th Grade Mathematics Achievement Score and Class Size
(n students=3,095; n classrooms=97; n teachers=77)

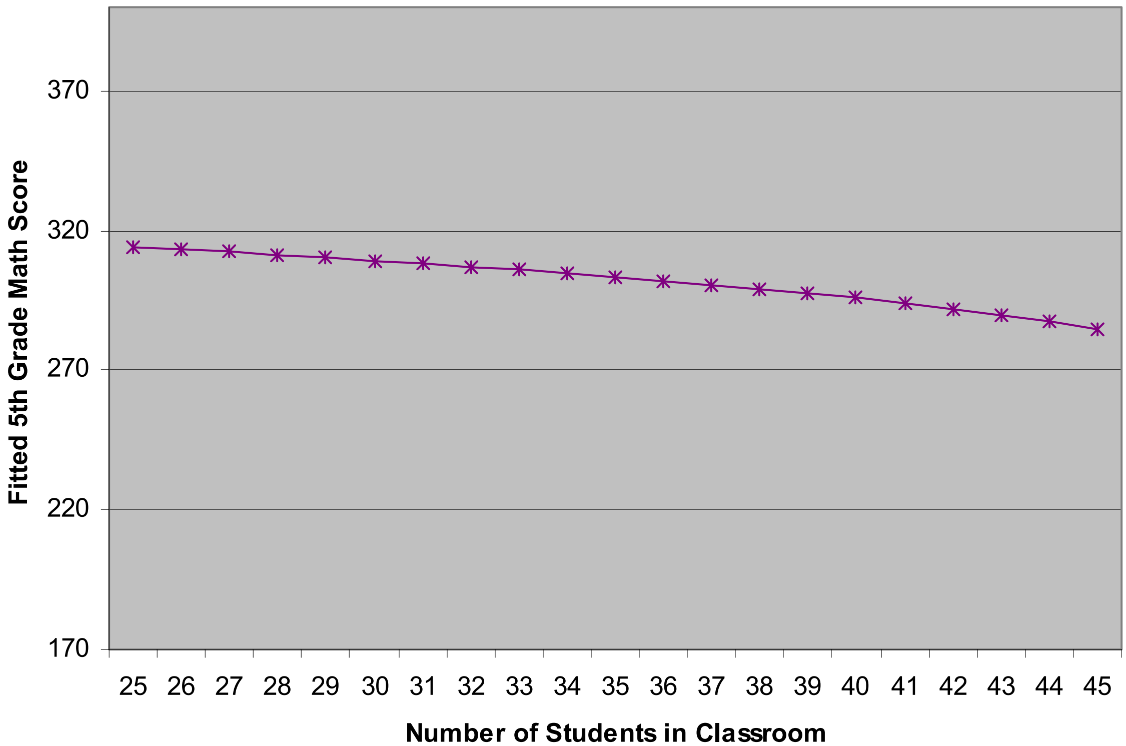


Figure 4
Effects of Classroom Peer-group Composition and Class Size on the Relative Ranking of the Teacher Fixed Effects (based on Models 2, 3 and 7)
(n students=3,095; n classrooms=97; n teachers=77)

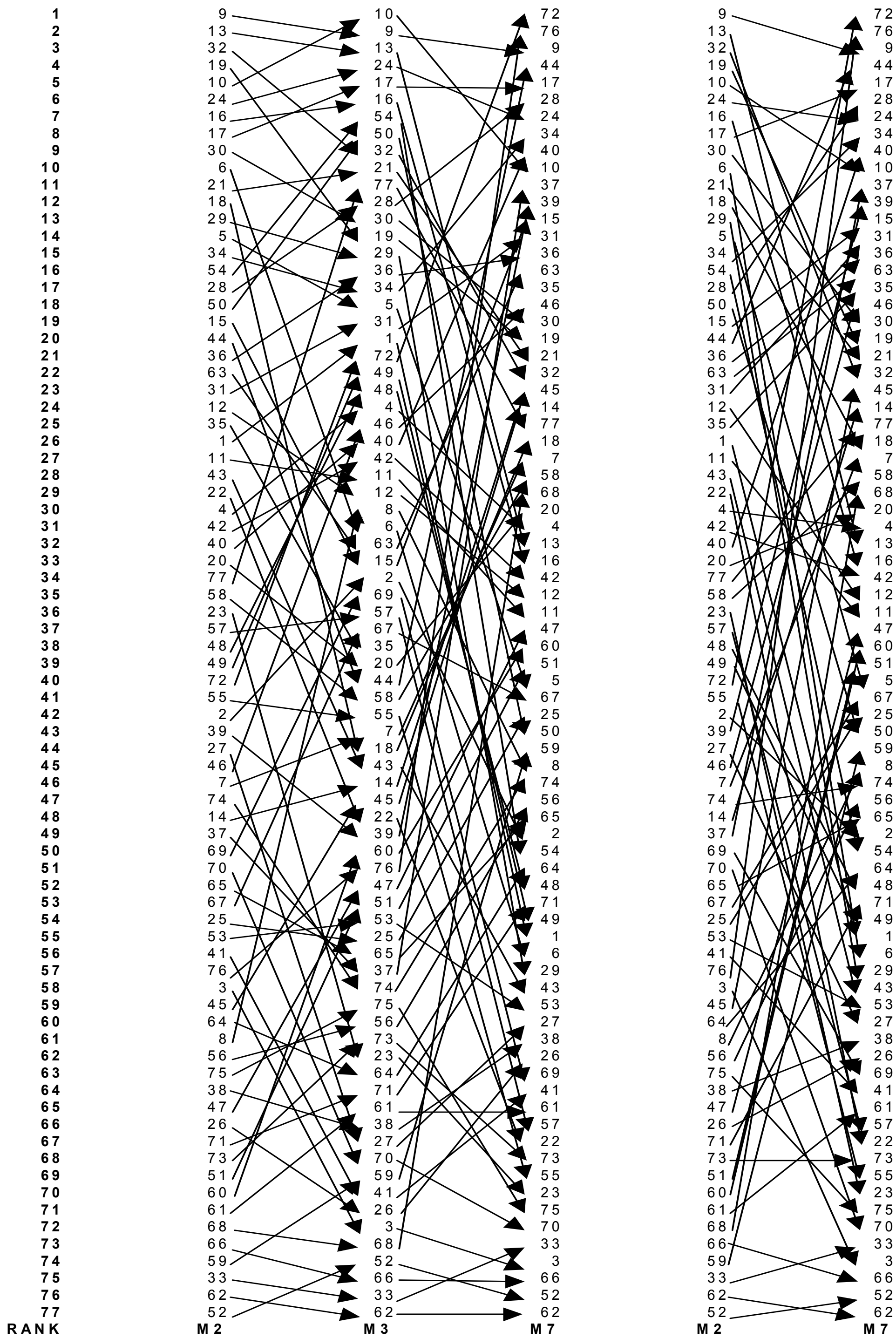


Figure 5
Distribution of Teacher Dummy Coefficients by Model Specification

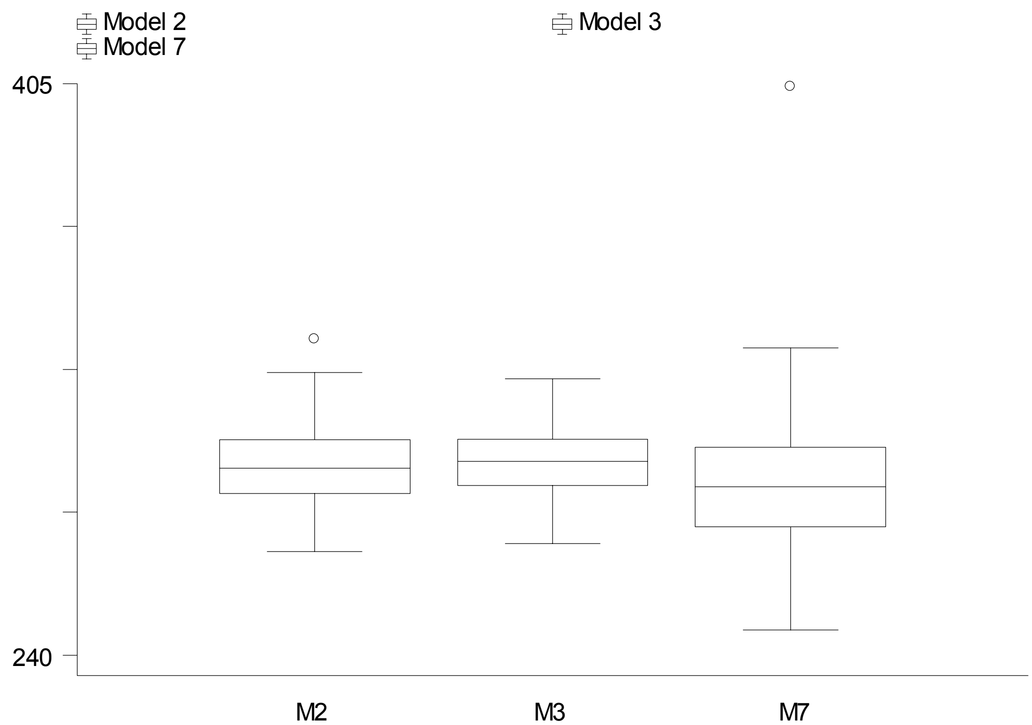


Figure 6
Scatter Plot of Teacher Fixed effects and Class Size
(based on Model 2c in Table 6)

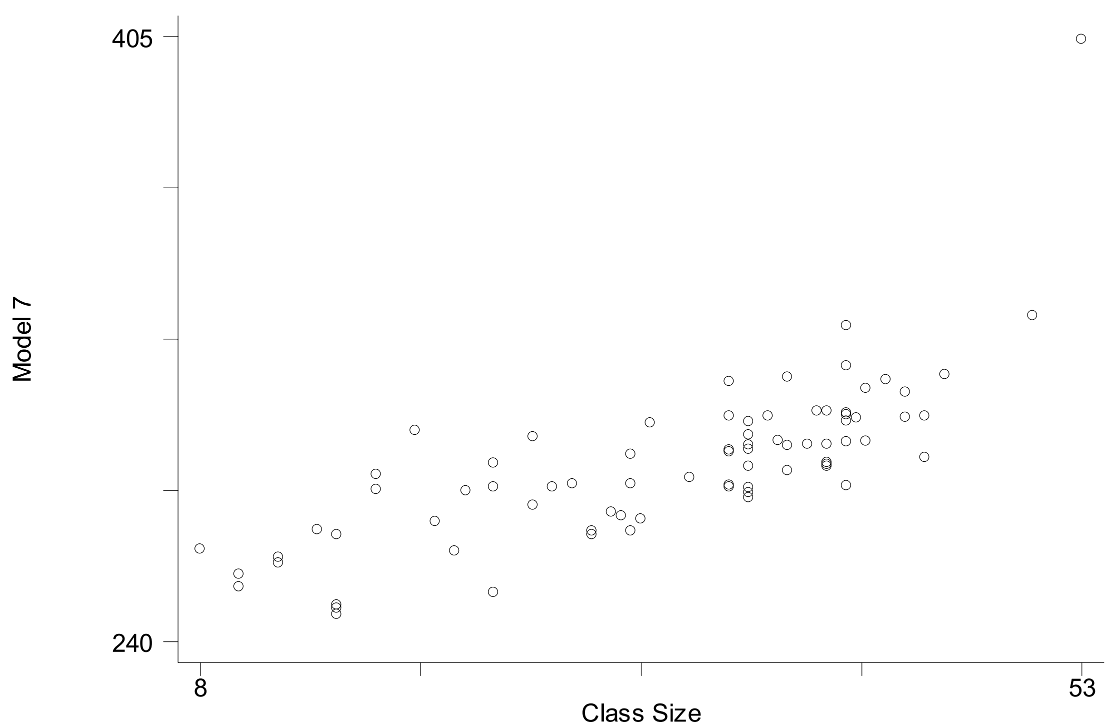
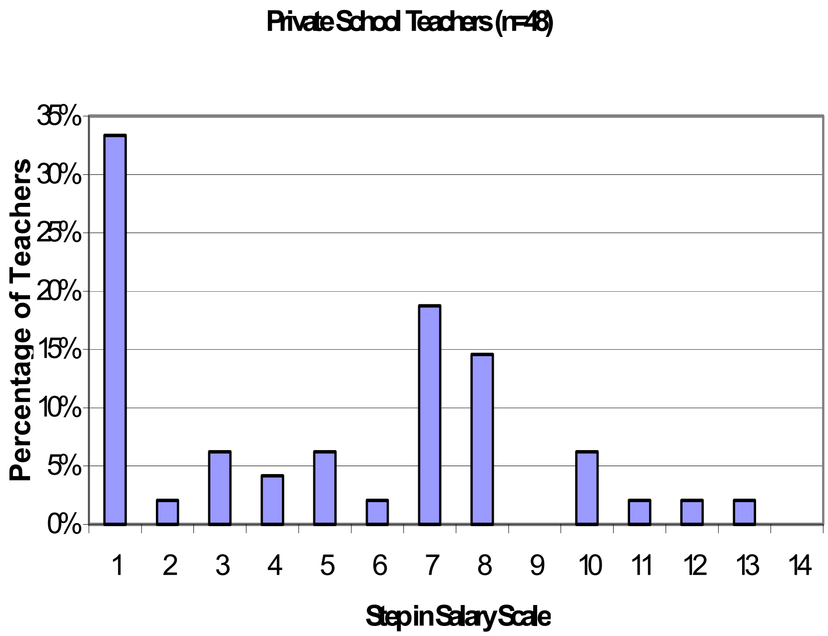


Figure 7
Distribution of Teachers in the Sample, by Step in the Salary Scale and Sector



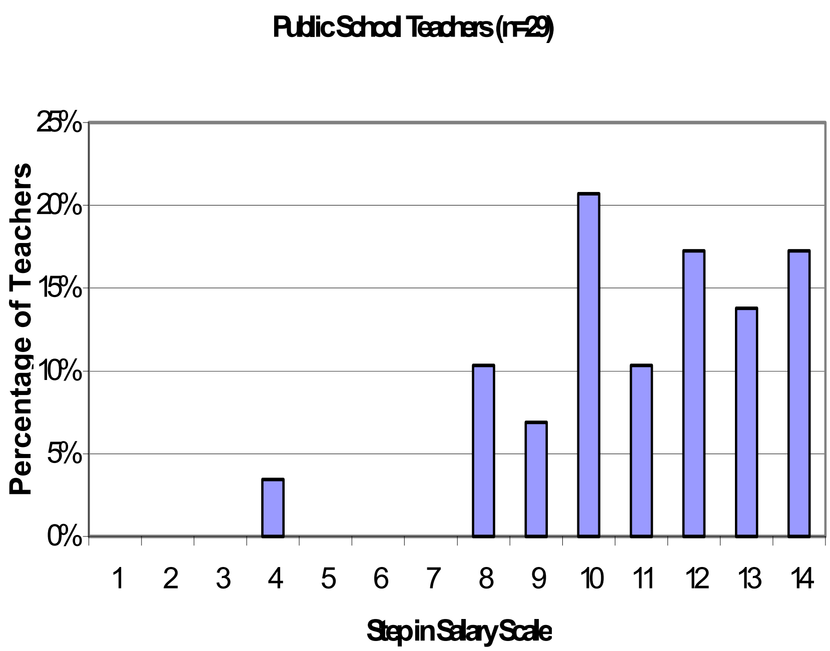


Table 7
Taxonomy of Classroom Random-Effects Regression Models Estimating the Effects of School Sector on Students' 5th grade Mathematics Achievement Score
(n students=3,095; n classrooms=97; n teachers=77)

	3a	**3b**	**3c (coefficient on Class Size constrained to its value in Model 2b (Table 6))**	**3d (coefficients on Class Size and CLMOTHED constrained to their values in Model 2c (Table 6))**
CONSTANT	292.310***	295.540***	298.140***	300.424***
STUDENT-LEVEL CONTROL PREDICTORS				
FORM	-6.782***	-6.447***	-6.401***	-6.359***
PRETEST		0.329***	0.318***	0.313***
PRETEST SQ		0.001***	0.001***	0.001***
FEMALE		-7.307***	-8.094***	-7.665***
AGE		-2.134**	-2.343***	-2.517***
AGE SQ		-1.005**	-0.873**	-0.922**
DAYABS		-1.938***	-1.896***	-1.866***
MHH		4.517***	4.660***	4.413***
BOOKS		2.683***	2.456***	2.460***
HWHELP1		7.603**	7.854**	7.697**
HWHELP2		7.348***	7.577***	7.531***
MOTHED		1.850*	1.244~	1.044
CLASS-LEVEL PREDICTORS				
CLMOTHED			(12.199)	(7.932)
CLASSIZE				(23.919)
SCHOOL SECTOR (PRIVATE=1)				
PRIVATE	**8.239***	**0.754**	**-3.789~**	**-14.502***
Goodness of Fit				
R^2 "within"	0.009	0.200	0.201	0.201
R^2 "between"	0.050	0.650	0.681	0.294
R^2 "overall"	0.025	0.290	0.316	0.195

~p<.10; *p<.05; **p<.01; ***p<.001

Figure 8
Distribution of Teacher Fixed Effects by Model Specification, by Sector
(panel B is based on 1b in Table 4; panel C is based on model 2b in Table 6; and panel D is based on Model 2c in Table 6)

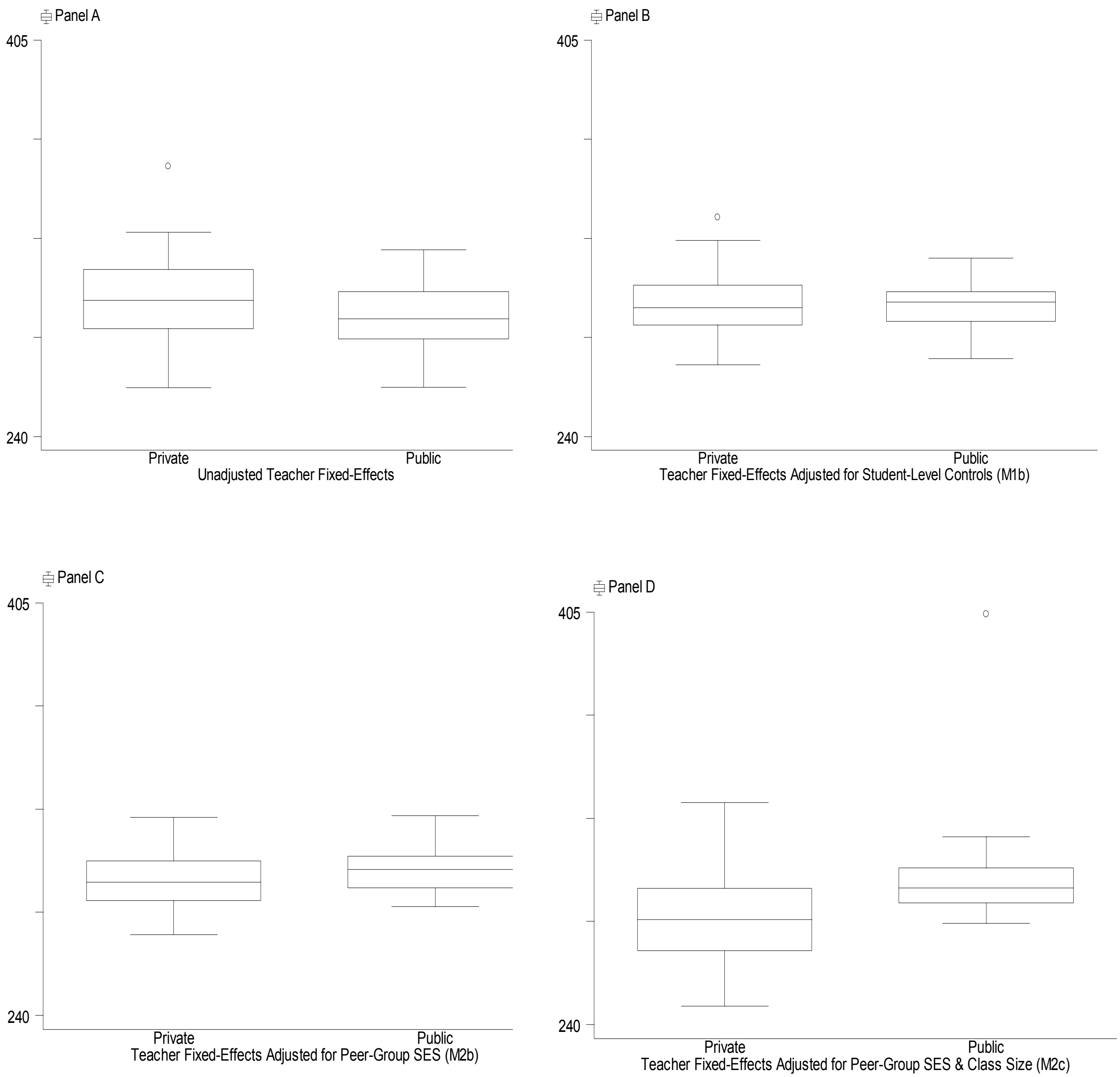


Table 8
Taxonomy of Fitted Constrained and Unconstrained Random-Effects Models Estimating the Effects of **Teacher Characteristics** on Students' 5th grade Mathematics Achievement Score
(n students=3,095; n classrooms =97; n teachers=77)

	CLASSROOM RANDOM-EFFECTS (with Class Size and CLMOTHED constrained to their values in Model 2c, Table 6)		**CLASSROOM RANDOM-EFFECTS (Unconstrained)**	
	4a	**4b**	**4c**	**4d**
CONSTANT	292.056***	277.394***	295.328***	293.681***
STUDENT-LEVEL CONTROL PREDICTORS				
FORM	-6.353***	-6.351***	-6.389***	-6.392***
PRETEST	0.311***	0.309***	0.313***	0.312***
PRETEST SQ	0.001***	0.001***	0.001***	0.001***
FEMALE	-7.809***	-7.882***	-8.512***	-8.524***
AGE	-2.570***	-2.561***	-2.417***	-2.400***
AGE SQ	-0.898**	-0.883**	-0.827*	-0.826*
DAYABS	-1.860***	-1.865***	-1.894***	-1.899***
MHH	4.469***	4.426***	4.801***	4.824***
BOOKS	2.442***	2.405***	2.388***	2.381***
HWHELP1	7.707**	7.662**	8.044**	8.024**
HWHELP2	7.568***	7.544***	7.712***	7.695***
MOTHED	0.998	0.899	1.055	1.042
CLASS-LEVEL PREDICTORS				
CLMOTHED	(7.932)	(7.932)	16.154***	15.694***
CLASSIZE	(23.919)	(23.919)	-0.802	-1.033
SCHOOL SECTOR (PRIVATE=1)				
PRIVATE	-12.695*		-1.603	
TEACHER PREDICTORS				
Teacher Years of Experience				
L_TEAXP	3.796	5.918*	0.097	0.327
Teacher Level of Education (Licensure or EDLEVEL3 omitted category)				
EDLEV1	-10.673	-11.842	-2.766	-2.840
EDLEV2	-23.592~	-27.053*	-2.345	-2.683
EDLEV4	-3.479	2.405	4.837~	5.438*
EDLEV5	5.107	3.233	-2.405	-2.838
Goodness of Fit				
R^2 "within"	0.201	0.201	0.201	0.201
R^2 "between"	0.420	0.273	0.697	0.697
R^2 "overall"	0.251	0.206	0.318	0.318

~p<.10; *p<.05; **p<.01; ***p<.001

Figure 9
Fitted Relationship between 5th Grade Mathematics Achievement Score and
Years of Teacher Experience for a Prototypical Student in a Classroom of Average Size and Peer-group SES
(from Model 4b in Table 8)
(n students = 3,095; n classrooms = 97; n teachers=77)