THREE ESSAYS IN MICROECONOMICS OF EDUCATION

by

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All errors are of course my own.

Contents

Contents – *Continued*

List of Figures

List of Tables

ABSTRACT

Education today is inseparable from the accumulation of human capital. *The New York Times* called human capital the most important asset in our portfolio. In my dissertation, I analyze the effectiveness of different educational policies and programs in Mexico and the United States.

In the first chapter of my dissertation I study the differences in the academic performance of students in the double-shift schooling system in Mexico. The double-shift schooling system is a common policy in countries with constrained resources. This policy is viewed as a way to serve more students. In Mexico, people believe that the morning shift provides better educational opportunities than the afternoon shift. This belief and, as a result, the excess demand for the morning shift have created a biased selection of better students into the morning session. The results suggest that a non-random assignment of students to schooling sessions explains the apparent academic inequality between students from different sessions.

The second chapter of my dissertation evaluates the Gifted and Talented Program in the elementary schools of TUSD. Gifted education and tracking ability programs have attracted a great deal of attention from education and economic researchers. However, there is no definite conclusion about the effects of these programs. In addition, the program placement is likely to be endogenous with respect to outcomes. The results suggest that there is a positive effect of the self-contained program, however, the instrumental variables estimation show no evidence of the effect.

In the third chapter I study school preferences under the open enrollment policy in the U. S. Some of the nation's largest districts are forced to close schools because of declines in student enrollment and budget cuts. Public schools are losing enrollment to charter schools. Moreover, under the open enrollment law students are opting

out to other, more attractive, neighboring districts. In order to keep schools open the school administration needs to understand what characteristics of schools would attract and keep students in schools. The results show that students are more likely to choose big schools in wealthier neighborhoods, with low mobility rates, and higher average scores.

Chapter 1

ACADEMIC PERFORMANCE IN DOUBLE-SHIFT SCHOOLING

1.1. Introduction

Double-shift or double-session schooling is a schooling system in which different cohorts of students use the same building and have the same academic curriculum, some in the mornings and some in the afternoons. Many developing countries, including Mexico, India, Brazil, Zimbabwe, Russia, Bulgaria, have adopted the double-shift schooling system. In the United States, in states such as Florida, a double-shift system is maintained due to the occurrence of natural disasters affecting the physical conditions of existing school buildings. In general, the purpose of double-shift schooling is to increase access to schooling while limiting strain on the budget.

From the policy perspective the introduction of double shifts allows existing sets of buildings and facilities to serve more students. This may be especially important in urban areas, where land is scarce and construction of new buildings is expensive. Double-shift schooling has helped many countries to move toward universal primary and secondary education. However, this policy may come at a cost. The limited school day under the multiple shift operation leaves few or no opportunities for any extra-curricular activities. In addition, there is some concern that students may be hurt by such policy. Afternoon students may receive a poorer education because of their tiredness by the time of classes or the diminishing productivity of teachers. The purpose of this study is to determine whether the difference in academic performance of students in the morning and afternoon shifts has a causal nature or is due to differences in characteristics of students as a result of the selection process.

Using a unique dataset from Mexico′s National Institute for Educational Assessment and Evaluation (INEE: *Instituto Nacional para la Evaluación de la Educación*), I examine factors influencing academic performance of students from different school shifts. More specifically, I focus on ninth grade students of secondary schools from morning and afternoon shifts and examine the effects of socio-economic and academic variables on students test score performance. To control for selection bias I employ the Heckman two-stage model. My key identification for the selection equations comes from exclusion restriction in which variable restricting school capacity determines the probability of a student getting into the morning session but not their performance on the tests. Furthermore, I apply the Oaxaca wage gap decomposition method to decompose the total effect into the effects of observed characteristics, returns to characteristics, and selection. In addition, I extend the analysis by decomposing the test difference due to observable characteristics into the three parts: due to the student, teacher, and school characteristics.

The results of my study reveal that there is no causal effect of the morning shift on the academic inequality of students from different shifts. Most of the test score difference can be explained by differences in the characteristics of students. The results also suggest that half of the math test score gap is due to differences in the observed characteristics of teachers. The findings of my research contribute an argument to the debate addressing the advantages and disadvantages of the double-shift schooling system. My results suggest that the double-shift schooling in Mexico serves its purpose by providing the equal education opportunities to all students.

1.2. Background and Literature Overview

Double-shift schooling (DSS) has been implemented in Mexico since the 1970s as a strategy to achieve universal access to basic education, given the lack of resources to fund construction of additional new school buildings. In this way the Mexican government has increased utilization of existing infrastructure by introducing morning, afternoon, and evening school shifts. Moreover, teachers have been given the opportunity to hold two teaching positions, thereby increasing their salaries. However, when schools reach their full capacity and begin to operate in two or three shifts, schools move away from learning communities where students spend longer periods of time and engage in extended sessions or extracurricular activities. In addition, the DSS system can create academic inequality between students from different shifts. In comparisons of means students from the morning shift perform better than students from the later shifts. The potential explanations for this difference in academic performance include less productive and/or less qualified teachers, tired and less attentive students, or negative peer effects in the afternoon shift.

Teachers often want to work to raise their earnings by working in more than one session, which may affect teacher instruction or teacher productivity. Educators in Mexico have been known as ″taxi teachers″ because many teachers jump into taxis at the end of the morning session in order to rush to teach an afternoon session elsewhere if they are not allowed to teach an additional session at the same school. One implication of ″shift work″ by many teachers is that they may be less effective educators in the afternoon. Unlike many professions where an individual worker performs a certain task or a few tasks during working hours, teachers must work outside their teaching hours without extra compensation. Teachers perform multiple tasks requiring specialization in areas such as educating students, monitoring student performance, and student discipline. In addition, many duties, such as preparing lesson plans, assignments, and grading, are performed outside the school and after working hours. Furthermore, teachers are generally required to teach more than one subject. Given the multiple tasks performed by a teacher, teacher performance may not be constant over the school day, the semester, or even the entire school year. As a result, a teacher's diminishing effectiveness in the classroom may affect students′ performance.

Students who attend the afternoon session spend their mornings studying, or performing house chores, or working to supplement family income. In rural areas, children generally help their families in field work. As a result, children attending afternoon school sessions may be at a disadvantage because they are tired and they may be less attentive to new learning.

Because of the perceived difference in academic performance between the different schooling shifts, goal-oriented parents and students seek the highest quality of education may prefer to attend the morning school session. However, the morning school sessions cannot accommodate all children. As a result selection decisions are made by the school administration. In general, student applicants with higher test scores in earlier year at their elementary schools are given higher priority for placement into the morning shift. Therefore, the test scores of students from the afternoon shifts, on average, are lower than the test scores of students from the morning shifts.

The literature on double-shift schooling is presented mostly by education practitioners. Existing works focus on the issues, problems, and benefits of the multiple shift schooling system. For example, Brey (2008) provides an overview of double-shift systems for students, teachers and school administrators. More specifically, Linden (2001) examines secondary schools that teach two sets of students in two shifts and concludes that double-shift schools appear to offer an adequate education and a solution for countries with resource constraints seeking to expand their secondary education systems.

Educational researchers in Mexico have turned their attention to the problems with DSS implementation. By analyzing differences in students′ and teachers′ distributions of characteristics, Cárdenas (2010) found that, on average, afternoon shift schools have lower levels of educational quality. His research shows that schools in the afternoon session have a higher proportion of low-income students and higher failure and dropout rates in comparison to morning shift schools sharing the same facilities. Saucedo Ramos (2005) describes a selection process which intentionally places repeaters and students with discipline problems into the afternoon session and shows that quality of instruction is lower in the afternoon than in the morning shift because of the different expectations and attitudes of teachers and principals. Using aggregate school data, Treviño Villarreal and Treviño González (2004) find the

Spanish scores of afternoon cohort students are significantly lower than the scores of morning shift students. Moreover, they show the importance of positive attitudes of teachers on the academic performance of students.

The literature on educators focuses on observable teacher characteristics such as experience, education, and certification. Santibañez (2006) indicates teacher test scores have a small positive relationship with average student achievement scores, although the effect is larger in secondary schools than in primary schools. Rivkin, Hanushek, and Kain (2005) find teachers in their first or second years of teaching are associated with lower student test scores in Texas, but teacher education and certification have no systematic relationship to student test score achievement. Betts, Zau, and Rice (2003) find mixed results for teacher characteristics using detailed individual-level data from elementary schools in the San Diego Unified School District. Rockoff (2004) shows teacher quality, measured by teacher fixed effects, have an important impact on student achievement. In other words, teacher quality may be important for students' performance; however, teacher productivity may be a detriment to students' performance when teachers work extended hours.

1.3. Education System in Mexico

According to the Constitution of Mexico, the objective of Mexican public education is compulsory education free of charge for every child. Since the Mexican Revolution of 1917, the basic goal of the government has been to increase educational coverage. Today, the Mexican education system serves over 30 million students and employs 1.6 million teachers in more than 229,000 schools and basic education enrollment has more than doubled from 9.7 million students in 1970 to 21.6 million students in 2000 (Razquin, Santibañez , Vernez (2005)). This rapid growth in basic education demand is primarily met by double shifting of schools and flexibility of teacher employment practices.

The Mexican education system is organized into four levels: preschool (K1–K3), compulsory basic education (grades 1–9), which includes primary and lower secondary education, upper secondary education (grades 10–12), and higher education. The government is officially responsible for providing compulsory basic education. The education system of Mexico also allows for the existence of private schools, but the public school system serves almost 90 percent of all students in the country. The delivery of basic education in Mexico takes different forms. However, ninety-three percent of primary education is delivered by general modality, a traditional approach that employs the Ministry of Education pre-approved universal national curriculum.

The Ministry of Education of Mexico (SEP: *Secretaría de Educación Pública*) is responsible for the country′s educational system; which includes setting guidelines for teacher salaries, along with the academic calendar year and the length of the school day. Specifically, all teachers are required to follow SEP′s national curriculum. Primary schools must use national textbooks, while secondary schools must choose textbooks from a nationally approved list. The school calendar generally is set to 200 days, beginning in August and ending in June of each calendar year. SEP specifies the length of each school day to four hours, allowing primary schools to operate regular sessions in multiple shifts: morning, afternoon, and sometimes evening. On the other hand, lower secondary schools operate in the mornings and afternoons, and each shift meets for five hours. In each regular shift, one-hour subjects include Spanish, mathematics, natural sciences, and social sciences. The consequences of operating multiple shifts and a limited school day leave few or no opportunities to study music or participate in extra-curricular activities such as sports, although some schools do make time for these subjects.

1.4. Identification Strategy

1.4.1. Main Model Framework

To identify factors that influence the academic performance of students, this study employs a model developed by Nakosteen and Zimmer (1980) to estimate migration decisions, using Heckman's (1979) two-stage estimation technique for sample selection bias. Specifically, the students in the sample are categorized into one of these two mutually exclusive regimes, with the selection equation serving as an endogenous selection criterion which determines the student′s shift.

Unlike the Nakosteen and Zimmer model, in which the migration decision is voluntary and based on an implicit cost-benefit analysis, this study's sorting function between morning and afternoon shifts involves both the choice of a student and the decision of the school administration. For simplicity, the analysis assumes every child (or their parents) prefers the morning shift, *ceteris parabus*. Although this assumption might not be completely true and there may be students who prefer the afternoon shift, the assumption is close to reality. One the instances of these reasons is the working schedule of parents. However, the fact that on average morning session grades are higher than afternoon grades makes the morning shift more desirable for students. In addition, the quality of teaching may be better in the morning, because teachers may not yet be tired, and therefore more effective in their teaching. As a result, excess demand for and limited capacity in the morning shift force students who cannot get into the morning cohort to be enrolled in the afternoon session. In fact, the unbalanced cohort size in the data reflects this situation.

Formally, at the beginning of middle school, student i wants to get into the morning shift if

$$S_i(M_i|X_i) - S_i(A_i|X_i) > F_i,$$

where $S(\cdot)$ is the score function of a student's family, representing the utility of schooling, M is an indicator variable that equals 1 if student i is in the morning shift and 0 otherwise, $A = 1 - M$, and X represents student, teacher, and school characteristics. The function F represents opportunity costs of the morning shift as a difference in expected scores. Furthermore, this function, which is assumed to be linear and additive, can be expressed as a function of characteristics, X, and an error term, v:

$$F_i = f(X_i) + v_i \tag{1.1}$$

Though the capacity for both shifts is the same when both shifts use the same schooling facilities, the school selection process in the morning session fills up to full capacity. Therefore, the enrollment in the morning shift, E_m, is equal to the full capacity of the school and the enrollment in the afternoon shift, E_a is less than or equal to the maximum capacity of the school. Since school capacity is different across schools, the ratio of morning to afternoon enrollment represents the degree to which capacity is constrained for the morning session. In other words, $W = \frac{E_m}{E_a}$ given the observed school characteristics should determine the probability that a student is admitted to the morning session. The sorting function can be modeled as

$$Prob(M_i = 1|X_i, W_i) = \Phi(Z_i'\gamma) \tag{1.2}$$

where $W_i \geq 1$ and $Z_i = (X_i, W_i)$.

Given the selection mechanism for students into the morning shift, the sorting equation is the function of gains in shifts$'$ scores and student, teacher, and school characteristics. Specifically, student i, with the vector of explanatory variables and excluded variables in the vector Z_i gets into the morning shift if

$$M_i^* > 0$$

and the afternoon shift if

$$M_i^* \leq 0$$

where

$$M_i^* = \alpha_0 + \alpha_1(S_{mi} - S_{ai}) + Z_i'\alpha_2 - \epsilon_i \tag{1.3}$$

The model is completed by the test score equations for morning and afternoon students as follows:

$$S_{mi} = X_{mi}'\beta_m + u_{mi} \tag{1.4}$$

$$S_{ai} = X'_{ai}\beta_a + u_{ai}, \tag{1.5}$$

where S_m and S_a are the performance scores for morning and afternoon students. The unobserved error terms ϵ is assumed to be a standard normal variable and u_m, u_a are unobserved error terms with means 0 and variances σ_m^2 and σ_a^2. In addition, the disturbance terms in equations (**??**), (**??**), and (**??**) are assumed to be jointly normally distributed with zero means and nonzero correlation between ϵ and u_m, ϵ and u_a.

We observe an indicator variable for the morning shift, defined as $M = 1$ if $M_i^* > 0$ and $M = 0$ if $M_i^* \leq 0$. In addition, we observe the scores for students in this certain shift, or $S = S_m$ when $M_i = 1$ and $S = S_a$ when $M_i = 0$.

Substituting equations (1.4) and (1.5) into equation (1.3) yields a reduced form of the sorting equation:

$$M_i^* = \gamma_0 + Z_i'\gamma_1 - \nu_i \tag{1.6}$$

where Z is the vector consisting of all exogenous variables in the model for both groups of students. Assuming that ν is normally distributed with mean zero and unit variance, the sorting equation above is estimated by the probit model.

Then, if we define $\psi_i = \gamma_0 + Z_i'\gamma_1$, the conditional means of the score disturbance terms do not equal zero, but vary with each observation, and differ for the morning and the afternoon cohort:

$$E(u_{mi}|M_i = 1) = \rho_{u_m\epsilon}\sigma_{u_m}\Big[\frac{-\phi(\psi)}{\Phi(\psi)}\Big] \tag{1.7}$$

$$E(u_{ai}|M_i = 0) = \rho_{u_a\epsilon}\sigma_{u_a}\Big[\frac{\phi(\psi)}{1 - \Phi(\psi)}\Big], \tag{1.8}$$

where $\rho_u\epsilon$ is the correlation between morning or afternoon respective u and ϵ, σ_{um} and σ_{ua} are the standard deviations of the disturbance terms of the two main score equations, and $\phi(\cdot)$ and $\Phi(\cdot)$ are the standard normal density and cumulative distribution functions, respectively.

1.4.2. Estimation Technique

The estimation of the score equations employs the ″Heckman Two-Step″ methodology. The first step runs a probit regression of the reduced form sorting equation (1.6) using all observations from both morning and afternoon shifts. The estimate of γ from the probit estimation is then used to obtain fitted values of $\hat{\psi}_i$ to construct consistent estimates of the Inverse Mills Ratio (IMR) for the morning shift

$$\hat{\lambda}_{mi} = \left[\frac{-\phi(\hat{\psi}_i)}{\Phi(\hat{\psi}_i)}\right]$$

and afternoon shift

$$\hat{\lambda}_{ai} = \left[\frac{\phi(\hat{\psi}_i)}{1 - \Phi(\hat{\psi}_i)}\right]$$

.

In the second stage, the outcome equations, including the IMR variable, are estimated by OLS technique, where the score equations are:

$$S_{mi} = X'_{mi}\beta_m + \theta_m\hat{\lambda}_{mi} + \eta_{mi} \tag{1.9}$$

$$S_{ai} = X'_{ai}\beta_a + \theta_a\hat{\lambda}_{ai} + \eta_{ai} \tag{1.10}$$

1.4.3. Test Score Gap Decomposition

Heckman′s two-stage estimation technique consistently estimates the parameters of the score equations. The unbiased estimators of the score equations can further be used to estimate the average expected score difference across students in different shifts. However, even after the selection bias correction, the average test score difference cannot explain the reasons why this difference still exists. The selection process allows us to see that on average the morning student is endowed with better characteristics. This might create unobservable peer effects. On the other hand, it is possible that differences in teacher characteristics can reinforce the positive effect of the academically advanced morning students or that the effect night be negated by the effect of bigger classes. In order to identify the nature of the test score gap I apply the methodology of Neuman and Oaxaca (2004) to the difference in expected test scores from different sessions.

The difference in expected values of test scores of the morning and afternoon shifts for a students i is:

$$\begin{aligned}\tau_i &= E(S_{mi}|X_{mi}, W_i, M_i = 1) - E(S_{ai}|X_{ai}, W_i, M_i = 0)\\ &= [X'_{mi}\beta_m + \theta_m\hat{\lambda}_{mi}] - [X'_{ai}\beta_a + \theta_a\hat{\lambda}_{ai}]\end{aligned}$$

Then the estimate of the overall difference in expected scores of different shifts, $\hat{\tau}$, is

$$\hat{\tau} = \frac{1}{n}\sum_{i=1}^{n}\hat{\tau}_i = (\overline{X}'_m\hat{\beta}_m - \overline{X}'_a\hat{\beta}_a) + (\hat{\theta}_m\overline{\hat{\lambda}}_m - \hat{\theta}_a\overline{\hat{\lambda}}_a) \tag{1.11}$$

where $\overline{X}$ is the mean vector of score determining the variables including a constant term, $\hat{\beta}$ is the vector of the estimated returns to the score determinants, $\hat{\theta}$ is the estimate of $\rho_{u\epsilon}\sigma_u$, and $\overline{\hat{\lambda}}$ is the mean of the Inverse Mills Ration estimated from the first stage of the selection equation.

Furthermore, the decomposition technique identifies the difference in the average scores between sessions due to the difference in characteristics, or explained gap, due to the returns to characteristics of students, teachers, and schools, or unexplained, and due to the selection process.

$$\hat{\tau} = \underbrace{(\overline{X}_m - \overline{X}_a)'\hat{\beta}_a}_{\text{explained gap}} + \underbrace{\overline{X}'_m(\hat{\beta}_m - \hat{\beta}_a)}_{\text{unexplained gap}} + \underbrace{(\hat{\theta}_m\overline{\hat{\lambda}}_m - \hat{\theta}_a\overline{\hat{\lambda}}_a)}_{\text{gap due to the selection}} \tag{1.12}$$

The explained gap, or the difference in expected score due to the difference in observed characteristics, can be further decomposed into the difference due to the students, teachers, and school characteristics.

$$
\begin{aligned}
(\overline{X}_m - \overline{X}_a)'\hat{\beta}_a = (\overline{X}_{m,student} - \overline{X}_{a,student})'\hat{\beta}_{a,student} \\
+ (\overline{X}_{m,teacher} - \overline{X}_{a,teacher})'\hat{\beta}_{a,teacher} \\
+ (\overline{X}_{m,school} - \overline{X}_{a,school})'\hat{\beta}_{a,school}
\end{aligned}
$$

Such fine decomposition can explain the exact source of the the difference in score gap if any.

1.5. Data Description

This paper employs the INEE dataset of standardized tests, administered by the SEP of Mexico to assess the general level of knowledge of students in both public and private schools throughout the country. The INEE was created by a presidential mandate on August 8th, 2002 as an independent organization to monitor and to assess the quality of the National Educational System.

The INEE collects information and conducts surveys to evaluate the students educational achievement and the general quality level of schools. The INEE collaborates with the The Organization for Economic Co-operation and Development (OECD) in the Programme for International Student Assessment (PISA) since 2000 and with the United National Educational, Scientific and Cultural Organization (UNESCO) in Second Regional Comparative and Explanatory Study (SERCE) since 2006. For the national education evaluation, the INEE developed Reviews of Quality and Educational Achievement (EXCALE: *Exámenes de la Calidad y el Logro Educativos*) in 2004.

The paper employs EXCALE–09. EXCALE–09 are datafiles containing a representative sample of ninth graders from lower secondary schools at the end of the 2007-2008 school year. The ninth grade signifies the last year for compulsory education; thereafter students have the option either to continue their education at the high school level or to end their schooling and enter the labor market.

The INEE administers paper-and-pencil tests to all ninth-grade students. The test format combines multiple-choice and open-ended questions. The test results are normalized and between 200 and 800. In addition to student test results, the INEE conducts survey questionnaires on personal characteristics with students, teachers, and school principals. Each student, teacher, and school is assigned a unique identifying code in the EXCALE dataset. Using these identifying codes I merge student test scores with their survey questionnaires. Personal student questionnaire contains many questions which allows me to pick a number of student characteristics to identify the parameters of their test score equations and control for the self selection as well as the identifying code of the school the student is in. Specifically, student characteristics include a student′s gender, age, parents' income, whether she lives with one or both parents, educational level of the student's parents and their occupational category, average number of hours a week the student spends studying outside of school, and whether the student is required with house chores.

Datasets containing the questionnaire answers of teachers and school principals have the school code that allows me to merge these datasets with the student information. The rich questionnaires allow me to handpick the teacher variables, such as her age, education level, and experience, the total number of hours the teacher works at a given school, whether she teaches one subject or more, and whether she teaches another shift or is employed outside of education.

Variables capturing the average number of hours a week a student spends helping her family, a dummy variable for whether a teacher teaches another shift or has another job. This variable may reveal whether a teacher teaching an additional shift diminishes teacher productivity and, thus, may be less effective as a teacher. In addition,when a child spends time helping the family it may cause a student to be fatigue and, thus, less attentive in the classroom.

The variables determining the probability that a student gets into the morning shift is the relative constraining capacity of the morning shift school, $\frac{E_m}{E_a}$. Since the number of students applying to the morning shift exceeds the capacity of the morning session, morning session enrollment must be higher than afternoon shift enrollment.

The Ministry of Education statistical data support this fact. On average, the ratio of urban school morning shift enrollment to afternoon enrollment sharing the same facilities is 2.18 with a standard deviation of 1.63.

The enrollment data for each school and other variable describing school characteristics are available in the principal′s questionnaire. Each different shift is assigned a unique, untraceable identification number. In other words, two different shifts sharing the same school building have two different identification numbers. As a result, it is not possible to identify in the INEE data whether two shifts are using the same school building. Using the publicly available data on Mexican schools I constructed a variable for constraining capacity of the morning shift, W_i. Upon special request, the research office of the INEE matched this variable to each school shift sharing the same building.

The excluded variable W for student i captures the morning shift enrollment constraint of a student's school relative to the afternoon shift enrollment. In other words, for the morning session students, the probability of getting into the morning shift increases in W_{ism}, holding everything else constant. Similarly, for students in the afternoon session, the exclusion restriction W_{isa} decreases in their school enrollment relative to the average morning enrollment. So, the probability of getting into the morning shift increases in W_{isa}. These excluded variables do not directly correlate with the academic performance of students. The school size and number of schools in the area depend on the local government budget and are therefore exogenous in the model. However, there may be worries that the shift enrollment correlates with the test scores, the outcome variable, through the class size or school quality. For instance, Angrist and Lavy (1999) find reducing class size induces an increase in test scores for fourth and fifth graders. Card and Krueger (1992) suggest reduction in the student-teacher ratio for elementary school students results in an increase in test scores on reading and math exams. Hence, school enrollment might be large or small, but potential success in a course strongly depends on the number of students in a class, or the teacher-student ratio. In order to control this potential correlation, a class size variable as a part of teacher questionnaire is included as a control variable in the analysis.

Other variables determining the school quality, such as the numbers of books and computers in the school, the existence of violence activity in the vicinity of the school, whether a school equipped for disabled students, if there is sport facility in a school, and if a school in the urban area are also included in the estimation. Therefore, holding school quality constant, the excluded variable W can serve as the determinant for sorting students into shifts.

The process of merging multiple datasets identified matching codes for only math and Spanish reading comprehension scores. The final samples for the analysis includes only students from public schools of general modality using double-shift system. Therefore, the compiled dataset for this study includes final math score sample of 2,579 students and the final Spanish score sample of 2,532 students with 1,367 and 1,308 students in the morning shift, respectively.

Summary statistics are reported in Tables 1.1 and 1.2. Since the data comes from the survey questionnaire the answers are categorical. Most of categorical answers are not linear in their values. In order to avoid any measurement errors and censoring problems in the analysis all variables are converted into the set of indicator variables. The first four columns of the table show the mean and the standard deviation of variables for morning and afternoon sessions. The last column reports the t-values for the test if the variables′ means of two groups of students are equal. The t-statistics show that most characteristics of morning group of students are very different from the characteristic of afternoon students. Specifically, morning students have higher average test score both in math and Spanish. They are younger than afternoon students which shows that there are more repeaters in the afternoon session who are less likely to get into the morning shift. Students from the morning shift come from the wealthier families and whose parents are more educated and work in the more professional positions. We can also see that morning classes are bigger on average and have more experienced teacher. Although, the summary statistics also shows that morning teachers are more likely to teach another shift and work more hours.

1.6. Regression Results

The first stage of the Heckman procedure involves estimation of a probit equation, where the dependent variable takes on the value 1 if the student is in the morning session and 0 if the student is in the afternoon session. Table 1.3 presents the results of this estimation on the math and Spanish samples respectively. The parameter of the constraining capacity of the morning school is positive and statistically significant for mathematics and Spanish scores. This implies the probability of getting into the morning shift increases with the increase in the constraining enrollment of a school, conditioning on a student and school characteristics. The sign of this excluded variable is as predicted by the model. In addition, the Chi-square test from the probit estimation indicates the assignment of students into various schooling shifts is not random. The estimates from the probit regressions are used to construct the Inverse Mills Ratio (IMR) to correct for selection bias in the estimation of the score equations.

Tables 1.4 and 1.5 report the estimated score equations on math and Spanish samples respectively. The first two columns present the results of the least square regressions, and other two columns present the results of the regressions with selectivity correction. Although, the coefficients on the IMR are not statistically significant the IMR still takes care of the selection into the shifts.

A number of the estimated coefficients on the variables of some categories that explain scores for the difference between two schooling shifts are not statistically significant. However a teacher teaching another shift has a positive effect on the math scores of students. This variable has less positive effect on the Spanish performance and the result is statistically significant only for morning session students. The sign of this variable is not as it was expected. This might be explained by the fact that a teacher teaching another shift gets a chance to practice his lecture more and presents it better. Interestingly, the teacher's hours of work has a negative effect on afternoon student's math score. This might be an evidence of the teacher$'$ diminishing productivity. However, the variable for a teacher working more than 35 hours a week has a positive influence on Spanish scores. A student spending more than three hours a week helping around the house has lower Math and Spanish scores in the afternoon shift although the effect is not statistically significant. Math score is higher for a students spending more time studying at home. Moreover, the magnitude for morning students is larger than for afternoon students. The same variable has also a positive effect on the Spanish score of students studying more hours a day, but the effect is larger for afternoon students.

The coefficient of the dummy variable for male students is positive and statistically significant in the Math equation and negative and statistically significant in the Spanish equation. This indicates that boys perform better in mathematics tests while girls perform better on tests of literacy and writing, which is consistent with the literature. Zembar and Blume (2009) show girls, on average, are better at spelling than boys and perform better on tests involving literacy, writing, and general knowledge, while boys, on average, perform better on mathematics tests in fourth grade.

Although no direct measure of a student family income exists in the dataset, a proxy variable is generated from the number of light bulbs and availability of internet access. Specifically, Sathaye and Meyers (1985) argue that wealthy families in developing countries live in larger homes and demand greater lighting of their houses than low-income households. In this study the number of light bulbs in a house, is positive and statistically significant for the families with 10 light bulbs and higher in a house, which is generally consistent with the results of other studies revealing the positive relationship between income and academic performance. The age of student coefficient is negative and statistically significant for the students in the afternoon shift, which indicates that students older than average ninth grader perform worse. Also, considering the selection process of students into the shifts, repeaters, or students older than their peers, are more likely to be in the afternoon shift. Therefore, the student's age has such a negative impact on the academic performance in the afternoon session.

Davis-Kean (2005) establishes a relationship between parents′ educational attainment and children′ academic achievement through parents′ educational expectations and parent-specific behaviors. My results show that mother's education has positive and statistically significant effect on academic performance of students rather than father's education. There is more effect of mother's education on math scores of morning students while there is no evidence of the effect on afternoon shift students. On the other hand, Spanish scores are positively related with the education of a mother in both shifts, although the magnitude of the effect is higher for morning students.

Larger class size has a more negative impact on math test performance than on Spanish. This may be explained by the difference in the nature of two subjects: math needs more concentration and individual approach which is less possible in beggar classes. Card and Krueger (1992) also show rate of returns to education are higher for individuals from states with better-educated teachers and with a higher fraction of female teachers. Although a number of studies show mixed results from a teacher′s experience on a student′s achievement scores, the less experienced teachers in this study show a positive effect on afternoon students′ performance in Spanish and negative effect on morning students′ performance in math.

The predicted total average score gap along with its decomposition are presented in Tables 1.6 and 1.7. The left panels of each table show the decomposition of the effect of the morning shift using a simple OLS specification. Uncorrected for selection, results show the average difference between morning and afternoon students. On average, morning students score about 42 points higher on math and about 46 points higher on Spanish reading comprehension tests which roughly translates to about 8 percent of the mean morning score. The decomposition results imply that not all of the difference is due to the unobserved effect of the school shift. More than a half of the score gap is explained by the differences in the observed characteristics of students, teachers, and schools. Moreover, the further decomposition of the explained gap shows us that the statistically significant effect is due to the difference in students and teachers variables.

The right panel of both tables presents the decomposition results corrected for the selection. Even though the results show students on average do better in the morning session than in the afternoon, the difference due to the returns to characteristics is not statistically different from zero. In other words, there is no evidence that the academic performance of students would be better in the morning school if students were randomly assigned to the different shifts. The implication is that most of the positive effect of going to the morning session may be due to the fact that better students get to the morning shift due to the assignment process. Most of this effect come from the difference in the observed characteristics, specifically from the characteristics of students. Of the total math score difference, about 17 points, or 3 percent of the mean morning math score can be explained by the difference in the characteristics of teachers, while Spanish scores do not depend on teacher characteristics. Math is the harder subject to teach and this may explain the greater importance of teacher. In both subjects the selection component of the test score gap is positive, although is not statistically significant.

The results indicate that if there were no difference in the characteristics of the average student from the morning and afternoon shifts, there would be no statistically significant effect of the morning shift. That is, the non-random assignment of the students into the shifts may be the reason of the apparent academic inequality between these two group of students. However, if the students were to be assigned to the shifts randomly, the difference between two schooling shift my be eliminated

1.7. Conclusion

The double-shift schooling system has been widely used to expand student enrollments and thereby to achieve the objective of ″Education for All.″ Despite the advantages of the double-shift schooling system, there may be negative externalities in academic achievement between the students from different schooling sessions. For instance, teacher effectiveness may decrease in the afternoon shift; which may lead to a reduction in the quality of teaching. In addition, students′ concentration may be lower in the afternoon, which in turn may affect the ability to learn new material and, thus, result in lower academic performance by students in the afternoon shift.

This paper examines the double-shift schooling system in Mexico, where the school administration assigns children to the different schooling sessions. The non-random assignment of children to different schooling shifts results in differences in the performance score gap between students in the morning and in the afternoon shifts. As a result, high ability students are granted admission into the morning shift, while low ability students are assigned to the afternoon session. As a result, these factors could result in an unequal distribution of educational opportunities across different groups of students.

This study analyzes academic performance of students from different schooling shifts using the Heckman selection model. The findings show a teacher working more hours yields a negative effect on students performance in both shifts. In addition, student studying is positive and statistically significant in the morning shift. However, most of the effect of the morning shift on academic achievement is due to the difference in the characteristics of students. In other words, the random assignment of students to the different schooling sessions may help to eliminate apparent average difference in the performance scores.

The importance of this research contributes to the debate of public policies and, moreover, the ways that government institutions address the consequences of the double-shift schooling system. In the case of Mexico, the double-shift schooling provides a solution to issues related to scarce resources and infrastructure limitations without creating inequalities in the quality of the education students receive between the two sessions.

1.8. Tables

Table 1.1: Summary Statistics for Math Score Sample

	Morning Shift		Afternoon Shift		Difference
Variable	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**	**in Means**
Relative Capacity	2.086	1.552	1.948	1.261	0.1381***
Student's Characteristics					
Average Math Score	524.553	94.535	482.630	80.834	41.9232***
Male	0.445	0.497	0.479	0.500	-0.0346*
Student's Age	15.147	0.464	15.460	0.697	-0.3129***
BothParents	0.793	0.405	0.762	0.426	0.0314**
Hours of Study:					
Not studying	0.020	0.139	0.029	0.168	-0.0091*
1 hour or less	0.298	0.457	0.376	0.485	-0.0785***
2 hours	0.391	0.488	0.357	0.479	0.0341*
3 hours	0.217	0.413	0.177	0.382	0.0399**
4 hours and more	0.074	0.262	0.060	0.238	0.0137
Hours of Help:					
Not helping	0.033	0.178	0.034	0.181	-0.0009
Less than 1 hour	0.137	0.344	0.128	0.334	0.0089
1 to 2 hours	0.429	0.495	0.389	0.488	0.0401**
3 hours and more	0.402	0.490	0.450	0.498	-0.0481**
Mother's education:					
No education	0.009	0.093	0.025	0.155	-0.0160***
1-3 grades	0.098	0.297	0.176	0.381	-0.0777***
3-6 grades	0.125	0.331	0.179	0.384	-0.0540***
7-9 grades	0.329	0.470	0.361	0.481	-0.0322
10-12 grades	0.243	0.429	0.182	0.386	0.0613***
Bachelor Degree	0.146	0.353	0.061	0.240	0.0845***
Graduate Degree	0.050	0.219	0.017	0.127	0.0340***
Father's education:					
No education	0.023	0.149	0.033	0.179	-0.0103
1-3 grades	0.085	0.279	0.158	0.365	-0.0736***

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Table 1.1 – *continued*

	Morning Shift		Afternoon Shift		Difference
Variable	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**	**in Means**
3-6 grades	0.101	0.301	0.145	0.352	-0.0443***
7-9 grades	0.274	0.446	0.324	0.468	-0.0507**
10-12 grades	0.257	0.437	0.209	0.407	0.0488***
Bachelor Degree	0.171	0.377	0.101	0.302	0.0697***
Graduate Degree	0.089	0.285	0.029	0.168	0.0604***
Mother′s ocupation:					
Not working	0.588	0.492	0.693	0.461	-0.1049***
Elementary occupation	0.048	0.214	0.060	0.238	-0.0120
Worker	0.023	0.151	0.037	0.189	-0.0137
Service employee	0.031	0.173	0.031	0.172	0.0002
Service provider	0.089	0.284	0.091	0.287	-0.0022
Clerical support worker	0.096	0.294	0.043	0.203	0.0529***
Associate professional	0.008	0.089	0.008	0.090	-0.0002
Professional	0.108	0.310	0.032	0.177	0.0754***
Manager	0.010	0.097	0.005	0.070	0.0046*
Father′s ocupation:					
Not working	0.023	0.149	0.043	0.203	-0.0202***
Elementary occupation	0.185	0.389	0.269	0.444	-0.0839***
Worker	0.162	0.369	0.197	0.398	-0.0348**
Service employee	0.164	0.370	0.164	0.371	-0.0003
Service provider	0.137	0.344	0.125	0.331	0.0114
Clerical support worker	0.082	0.274	0.059	0.236	0.0225**
Associate professional	0.049	0.216	0.059	0.236	-0.0104
Professional	0.175	0.380	0.065	0.247	0.1097***
Manager	0.023	0.151	0.017	0.131	0.0061
Number of Light Bulbs in the house:					
0-3	0.050	0.217	0.073	0.261	-0.0237***
4-5	0.120	0.325	0.198	0.399	-0.0780***
6-7	0.181	0.385	0.224	0.417	-0.0437***

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Table 1.1 – *continued*

	Morning Shift		**Afternoon Shift**		**Difference**
Variable	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**	**in Means**
8-9	0.209	0.407	0.209	0.407	0.0005
10-15	0.261	0.439	0.194	0.396	0.0673***
16-25	0.119	0.324	0.074	0.262	0.0450***
26 and more	0.060	0.238	0.027	0.163	0.0328***
Internet	0.371	0.483	0.225	0.418	0.1456***
Teacher's Characteristics					
Class Size:					
41 students and more	0.285	0.452	0.141	0.348	0.1442 ***
26-41 students	0.675	0.468	0.600	0.490	0.0754 ***
16-25 students	0.029	0.167	0.235	0.424	-0.2066***
15 students and less	0.011	0.104	0.024	0.153	-0.0130**
Experience:					
Less than 2 years	0.018	0.134	0.062	0.241	-0.0436***
3-10 years	0.196	0.397	0.304	0.460	-0.1076***
11-15 years	0.206	0.405	0.165	0.371	0.0413 **
16 years and more	0.579	0.494	0.469	0.499	0.1099 ***
Hours of work:					
5 hours and less	0.025	0.156	0.076	0.265	-0.0510***
6-16 hours	0.112	0.315	0.185	0.388	-0.0729***
17-34 hours	0.304	0.460	0.376	0.485	-0.0719***
35 hours and more	0.559	0.497	0.363	0.481	0.1959 ***
Age:					
29 and younger	0.050	0.217	0.125	0.331	-0.0757***
30-39 years	0.229	0.420	0.244	0.430	-0.0153
40-49 years	0.421	0.494	0.450	0.498	-0.0283
50 and older	0.300	0.458	0.181	0.385	0.1192***
Teaching 1 subject	0.797	0.402	0.766	0.424	0.0317
College degree	0.206	0.405	0.178	0.383	0.0281
Additional Shift	0.282	0.450	0.232	0.422	0.0505***

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Table 1.1 – *continued*

	Morning Shift		Afternoon Shift		Difference
Variable	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**	**in Means**
Has Another Job	0.901	0.299	0.885	0.319	0.0152
School Characteristics					
Violence in vicinity	0.458	0.498	0.468	0.499	-0.0099
Number of Books:					
100 and less	0.045	0.207	0.111	0.315	-0.0668***
100-200	0.094	0.291	0.125	0.331	-0.0318***
200-400	0.176	0.381	0.184	0.388	-0.0084
400 and more	0.686	0.464	0.579	0.494	0.1070***
Number of Computers:					
No computers	0.090	0.286	0.090	0.286	0.00004
10 and less	0.154	0.361	0.186	0.390	-0.0321***
11-30	0.556	0.497	0.530	0.499	0.0263
31-50	0.103	0.304	0.126	0.332	-0.0231
50 and more	0.097	0.295	0.068	0.251	0.0289***
Disability Facility	0.143	0.351	0.125	0.330	0.0188**
Sport Facility	0.876	0.330	0.865	0.342	0.0110
Urban	0.977	0.151	0.965	0.183	0.0112
N	1,367		1,212		

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 1.2: Summary Statistics for Spanish Score Sample

	Morning Shift		**Afternoon Shift**		**Difference**
Variable	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**	**in Means**
Relative Capacity	2.005	1.478	2.015	1.330	-0.0098
Student′s Characteristics					
Average Spanish Score	525.264	92.461	479.536	86.314	45.7273 ***
Male	0.438	0.496	0.513	0.500	-0.0750***
Student′s Age	15.157	0.474	15.456	0.704	-0.2991***
BothParents	0.818	0.386	0.740	0.439	0.0778***
Hours of Study:					
Not studying	0.013	0.113	0.028	0.164	-0.0148***
1 hour or less	0.320	0.466	0.378	0.485	-0.058***
2 hours	0.367	0.482	0.385	0.487	-0.0178
3 hours	0.199	0.399	0.158	0.365	0.0411***
4 hours and more	0.102	0.302	0.051	0.221	0.0502 ***
Hours of Help:					
Not helping	0.042	0.201	0.038	0.190	0.0045
Less than 1 hour	0.144	0.352	0.132	0.339	0.0121
1 to 2 hours	0.454	0.498	0.404	0.491	0.0497**
3 hours and more	0.359	0.480	0.426	0.495	-0.0663
Mother′s education:					
No education	0.011	0.103	0.036	0.186	-0.0252***
1-3 grades	0.091	0.288	0.174	0.379	-0.0830***
3-6 grades	0.136	0.343	0.194	0.396	-0.0584***
7-9 grades	0.297	0.457	0.349	0.477	-0.0522***
10-12 grades	0.264	0.441	0.154	0.361	0.1102***
Bachelor Degree	0.151	0.359	0.064	0.244	0.0877***
Graduate Degree	0.050	0.219	0.029	0.169	0.0210***
Father′s education:					
No education	0.015	0.120	0.027	0.162	-0.0124**
1-3 grades	0.081	0.273	0.126	0.332	-0.0448***

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Table 1.2 – *continued*

	Morning Shift		Afternoon Shift		Difference
Variable	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**	**in Means**
3-6 grades	0.109	0.312	0.175	0.380	-0.0655***
7-9 grades	0.291	0.455	0.349	0.477	-0.0576***
10-12 grades	0.232	0.423	0.203	0.403	0.0290*
Bachelor Degree	0.206	0.405	0.088	0.284	0.1182***
Graduate Degree	0.065	0.247	0.032	0.176	0.0331***
Mother′s ocupation:					
Not working	0.609	0.488	0.690	0.463	-0.0802***
Elementary occupation	0.044	0.206	0.058	0.234	-0.0137
Worker	0.025	0.157	0.037	0.188	-0.0115*
Service employee	0.022	0.147	0.051	0.219	-0.0285***
Service provider	0.083	0.275	0.071	0.257	0.0115
Clerical support worker	0.099	0.298	0.051	0.221	0.0472***
Associate professional	0.005	0.073	0.007	0.085	-0.0020
Professional	0.103	0.304	0.033	0.178	0.0705***
Manager	0.009	0.095	0.002	0.049	0.0067**
Father′s ocupation:					
Not working	0.025	0.157	0.038	0.192	-0.0132*
Elementary occupation	0.158	0.365	0.264	0.441	-0.1056***
Worker	0.163	0.369	0.206	0.405	-0.0430***
Service employee	0.184	0.388	0.207	0.405	-0.0224
Service provider	0.146	0.353	0.113	0.316	0.0333**
Clerical support worker	0.080	0.271	0.045	0.207	0.0346***
Associate professional	0.060	0.237	0.049	0.216	0.0106
Professional	0.163	0.369	0.060	0.238	0.1024***
Manager	0.021	0.145	0.018	0.133	0.0034
Number of Light Bulbs in the house:					
0-3	0.037	0.190	0.079	0.270	-0.0418***
4-5	0.122	0.327	0.192	0.394	-0.0704***
6-7	0.170	0.376	0.246	0.431	-0.0754***

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Table 1.2 – *continued*

	Morning Shift		Afternoon Shift		Difference
Variable	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**	**in Means**
8-9	0.214	0.410	0.197	0.398	0.0172
10-15	0.288	0.453	0.181	0.385	0.1077***
16-25	0.125	0.331	0.073	0.260	0.0527***
26 and more	0.043	0.203	0.033	0.178	0.0101
Internet	0.364	0.481	0.203	0.402	0.1613***
Teacher's Characteristics					
Class Size:					
41 students and more	0.319	0.466	0.109	0.311	0.2101***
26-41 students	0.652	0.476	0.632	0.483	0.0206
16-25 students	0.018	0.131	0.237	0.425	-0.2193***
15 students and less	0.011	0.107	0.023	0.150	-0.0114**
Experience:					
Less than 2 years	0.035	0.184	0.057	0.232	-0.0220***
3-10 years	0.198	0.399	0.237	0.425	-0.0389**
11-15 years	0.196	0.397	0.176	0.381	0.0200
16 years and more	0.570	0.495	0.529	0.499	0.0409**
Hours of work:					
5 hours and less	0.063	0.244	0.114	0.318	-0.0509***
6-16 hours	0.148	0.355	0.184	0.387	-0.0363**
17-34 hours	0.318	0.466	0.377	0.485	-0.0594***
35 hours and more	0.471	0.499	0.324	0.468	0.1466***
Age:					
29 and younger	0.079	0.269	0.089	0.285	-0.0103
30-39 years	0.213	0.409	0.223	0.416	-0.0105
40-49 years	0.507	0.500	0.447	0.497	0.0600***
50 and older	0.202	0.402	0.241	0.428	-0.0392**
Teaching 1 subject	0.864	0.343	0.815	0.389	0.0494***
College degree	0.147	0.354	0.123	0.329	0.0234*
Additional Shift	0.285	0.452	0.270	0.444	0.0147

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Table 1.2 – *continued*

Variable	Morning Shift Mean	Morning Shift Std. Dev.	Afternoon Shift Mean	Afternoon Shift Std. Dev.	Difference in Means
Has Another Job	0.957	0.203	0.906	0.292	0.0511***
School Characteristics					
Violence in vicinity	0.497	0.500	0.477	0.500	0.0198
Number of Books:					
100 and less	0.047	0.213	0.115	0.319	-0.0678***
100-200	0.102	0.302	0.122	0.327	-0.0201
200-400	0.177	0.381	0.177	0.382	-0.0007
400 and more	0.674	0.469	0.586	0.493	0.0885***
Number of Computers:					
No computers	0.089	0.284	0.102	0.303	-0.0134
10 and less	0.167	0.373	0.195	0.397	-0.0286*
11-30	0.528	0.499	0.511	0.500	0.0169
31-50	0.115	0.319	0.124	0.330	-0.0095
50 and more	0.102	0.303	0.068	0.252	0.0346***
Disability Facility	0.153	0.360	0.132	0.338	0.0214
Sport Facility	0.846	0.361	0.862	0.345	-0.0156
Urban	0.976	0.152	0.958	0.200	0.0180**
N	1,308		1,224		

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 1.3: First Stage Probit Estimates

	Math Sample		**Spanish Sample**	
	Coefficient	**Std. Error**	**Coefficient**	**Std. Error**
Relative Capacity	0.1621***	0.0588	0.1243**	0.0557
Student's Characteristics				
Male	-0.0583	0.0580	-0.1665***	0.0468
Student's Age	-0.4528***	0.0668	-0.3882***	0.0587
BothParents	0.1314	0.0824	0.3223***	0.0965
Hours of Study:				
1 hour or less	0.2462	0.1702	0.3577*	0.2170
2 hours	0.4040**	0.1682	0.4457**	0.2105
3 hours	0.4522**	0.1831	0.6126**	0.2452
4 hours and more	0.4626**	0.1891	0.8887***	0.2429
Hours of Help:				
Less than 1 hour	-0.0302	0.1585	-0.0621	0.1704
1 to 2 hours	-0.0262	0.1678	-0.1460	0.1536
3 hours and more	-0.1056	0.1692	-0.2281	0.1668
Mother's education:				
1-3 grades	0.3402	0.2815	0.3066	0.2326
3-6 grades	0.3426	0.2939	0.5161**	0.2316
7-9 grades	0.4091	0.2983	0.4920**	0.2477
10-12 grades	0.4609	0.2932	0.7639***	0.2459
Bachelor Degree	0.6125**	0.2954	0.7452***	0.2427
Graduate Degree	0.6190*	0.3273	0.3833	0.3417
Father's education:				
1-3 grades	-0.3272	0.2242	-0.0793	0.2690
3-6 grades	-0.2299	0.1969	-0.2011	0.2746
7-9 grades	-0.1796	0.1896	-0.0855	0.2446
10-12 grades	-0.1906	0.1885	-0.1236	0.2475
Bachelor Degree	-0.2732	0.1885	-0.0660	0.3025
Graduate Degree	-0.1249	0.2387	-0.1732	0.3391
Mother's ocupation:				
Elementary occupation	0.1726	0.1471	0.0757	0.1237
Worker	-0.1625	0.2016	-0.0034	0.1937
Service employee	0.1072	0.2030	-0.3342**	0.1355

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Table 1.3 – *continued*

	Math Sample		**Spanish Sample**	
	Coefficient	**Std. Error**	**Coefficient**	**Std. Error**
Service provider	-0.0167	0.1237	-0.0136	0.1190
Clerical support worker	0.4666***	0.1354	0.2385*	0.1360
Associate professional	-0.0772	0.2641	-0.5686	0.3461
Professional	0.2416	0.1843	0.3271**	0.1471
Manager	0.0588	0.4167	0.7634	0.5350
Father′s ocupation:				
Elementary occupation	0.1475	0.1476	-0.0179	0.1542
Worker	0.1353	0.1554	-0.0001	0.1718
Service employee	0.2817*	0.1585	0.0601	0.1601
Service provider	0.2379	0.1517	0.1372	0.1482
Clerical support worker	0.2097	0.1879	0.2339	0.2370
Associate professional	0.0053	0.1757	0.1566	0.2071
Professional	0.4965***	0.1886	0.3836	0.2554
Manager	0.3979	0.2475	0.0829	0.3446
Number of Light Bulbs in the house:				
4-5	-0.0786	0.1390	-0.0667	0.1665
6-7	-0.0580	0.1547	-0.1073	0.1324
8-9	0.0535	0.1330	0.0336	0.1531
10-15	0.1171	0.1431	0.2153	0.1600
16-25	0.0593	0.1635	0.0980	0.2093
26 and more	0.2983	0.2229	-0.1289	0.2446
Internet	0.1376	0.0928	0.1251	0.0868
Teacher′s Characteristics				
Class Size:				
26-41 students	-0.4137**	0.2025	-0.6458***	0.2129
16-25 students	-1.7917***	0.3620	-2.1497***	0.3813
15 students and less	-0.8389	0.6487	-0.9653	0.6662
Experience:				
3-10 years	-0.0272	0.3869	-0.0090	0.5030
11-15 years	0.2763	0.3945	0.0235	0.5342
16 years and more	0.1518	0.4250	0.0394	0.5484
Hours of work:				

Continued on next page

Table 1.3 – *continued*

	Math Sample		**Spanish Sample**	
	Coefficient	**Std. Error**	**Coefficient**	**Std. Error**
6-16 hours	0.4975*	0.2901	0.1759	0.3424
17-34 hours	0.5851**	0.2721	0.2070	0.3356
35 hours and more	0.8621***	0.2536	0.3460	0.3204
Age:				
30-39 years	0.4816	0.3133	0.0344	0.3491
40-49 years	0.3155	0.3509	0.1665	0.3426
50 and older	0.6205	0.4037	-0.1146	0.3779
Teaching 1 subject	0.1598	0.1711	0.1646	0.2531
College degree	0.0440	0.2151	0.3256	0.2100
Additional Shift	0.3352*	0.1995	0.1369	0.1869
Has Another Job	0.2067	0.2324	0.3596	0.3094
School Characteristics				
Violence in vicinity	-0.0627	0.1617	0.1503	0.1534
Number of Books:				
100-200	0.5291	0.4136	0.6132	0.4917
200-400	0.5944*	0.3130	0.5812	0.3982
400 and more	0.6561**	0.3058	0.5539	0.3920
Number of Computers:				
10 and less	-0.0924	0.3505	0.2150	0.3475
11-30	0.0392	0.3042	0.2296	0.3448
31-50	-0.2144	0.3780	-0.0747	0.3629
50 and more	-0.1390	0.4124	0.0937	0.4758
Disability Facility	-0.1196	0.2701	-0.1875	0.2595
Sport Facility	0.0014	0.3242	-0.1037	0.2649
Urban	0.1857	0.4614	0.4515	0.5130
Constant	3.9371***	1.4920	3.3374**	1.5735
N	2,579		2,532	
Presudo R^2	0.247		0.257	

Standard errors are bootstrapped and clustered at school level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.4: Regression Results of Average Math Test Scores

Variable	**OLS** Morning Shift	**OLS** Afternoon Shift	**Heckman Estimation** Morning Shift	**Heckman Estimation** Afternoon Shift
Student′s Characteristics				
Male	13.356***	8.595*	12.580**	8.919*
	(5.068)	(4.608)	(5.209)	(4.716)
Student′s Age	-1.792	-15.726***	-6.989	-13.078***
	(5.394)	(3.333)	(8.718)	(4.709)
BothParents	3.551	15.310***	4.800	13.990**
	(6.219)	(5.467)	(7.123)	(4.930)
Hours of Study:				
1 hour or less	28.772	8.125	31.357*	6.870
	(18.274)	(13.674)	(17.351)	(13.513)
2 hours	53.342***	23.251*	57.900***	20.704
	(5.936)	(5.111)	(17.762)	(13.582)
3 hours	56.653***	44.685***	61.486***	42.041***
	(6.125)	(5.905)	(19.081)	(13.744)
4 hours and more	77.518***	16.497	82.308***	13.490
	(9.444)	(9.456)	(20.034)	(16.126)
Hours of Help:				
Less than 1 hour	46.836***	-7.676	46.822***	-6.807
	(15.018)	(13.495)	(11.963)	(12.987)
1 to 2 hours	27.550*	6.990	27.457*	7.693
	(7.056)	(6.632)	(10.090)	(12.273)
3 hours and more	26.149*	-2.510	25.177*	-0.982
	(5.078)	(4.512)	(10.324)	(12.287)
Mother′s education:				
1-3 grades	45.643	11.238	50.553*	8.924
	(28.685)	(15.314)	(27.120)	(18.180)
3-6 grades	44.616	10.188	49.771*	8.022
	(10.501)	(7.412)	(27.008)	(18.655)
7-9 grades	43.359	9.998	49.762*	7.565

Continued on next page

Table 1.4 – *continued*

Variable	OLS Morning Shift	OLS Afternoon Shift	Heckman Estimation Morning Shift	Heckman Estimation Afternoon Shift
	(6.876)	(5.478)	(26.987)	(18.019)
10-12 grades	53.763*	25.207	60.691**	22.182
	(6.647)	(6.385)	(27.706)	(19.122)
Bachelor Degree	76.439***	31.764*	84.974***	27.370
	(8.496)	(10.534)	(29.287)	(21.033)
Graduate Degree	55.236*	14.662	63.299**	10.112
	(13.672)	(20.578)	(33.655)	(28.669)
Father′s education:				
1-3 grades	7.636	1.176	3.104	3.512
	(18.341)	(13.365)	(20.430)	(12.361)
3-6 grades	2.963	5.487	-0.419	6.541
	(10.681)	(7.724)	(18.783)	(12.990)
7-9 grades	17.050	-3.402	14.322	-2.306
	(7.254)	(5.530)	(17.921)	(12.390)
10-12 grades	29.874	2.831	27.218	3.792
	(6.365)	(5.798)	(18.286)	(13.201)
Bachelor Degree	35.197*	10.472	31.716	12.013
	(8.348)	(8.623)	(20.614)	(15.028)
Graduate Degree	18.368	-1.571	16.326	-1.331
	(9.839)	(14.133)	(21.660)	(24.790)
Mother′s ocupation:				
Elementary occupation	15.092	4.713	16.970	3.151
	(11.794)	(9.444)	(14.266)	(8.223)
Worker	13.299	19.294	11.426	20.101*
	(16.352)	(11.801)	(19.648)	(12.288)
Service employee	17.639	12.708	17.787	11.941
	(14.335)	(12.855)	(14.127)	(14.528)
Service provider	19.347**	23.156***	18.567**	23.073***
	(9.046)	(7.901)	(10.502)	(9.137)
Clerical support worker	-0.672	20.837*	3.995	17.429

Continued on next page

Table 1.4 – *continued*

Variable	OLS Morning Shift	OLS Afternoon Shift	Heckman Estimation Morning Shift	Heckman Estimation Afternoon Shift
	(8.447)	(11.060)	(10.569)	(12.732)
Associate professional	-16.322	-9.101	-17.960	-8.429
	(27.306)	(24.838)	(29.468)	(26.870)
Professional	-8.968	6.897	-7.351	4.318
	(8.858)	(12.849)	(12.386)	(16.560)
Manager	-25.718	18.606	-24.277	16.216
	(25.424)	(33.396)	(23.809)	(26.510)
Father′s ocupation:				
Elementary occupation	-14.806	-15.808	-12.960	-16.568
	(17.124)	(11.409)	(23.432)	(12.092)
Worker	-16.253	1.039	-14.701	0.480
	(8.111)	(6.419)	(23.089)	(12.212)
Service employee	-16.672	-22.192*	-13.837	-23.661*
	(7.283)	(6.258)	(23.306)	(11.745)
Service provider	-14.898	-13.946	-12.392	-15.290
	(7.593)	(6.864)	(24.692)	(13.558)
Clerical support worker	-19.327	-0.927	-16.844	-1.806
	(9.146)	(9.435)	(24.006)	(15.733)
Associate professional	-47.299**	-25.468*	-48.009**	-25.107*
	(11.406)	(9.392)	(24.567)	(15.524)
Professional	3.799	-23.759	8.673	-27.137*
	(6.775)	(9.021)	(25.213)	(17.617)
Manager	-21.667	-27.619	-17.802	-29.436
	(16.270)	(16.871)	(28.303)	(28.710)
Number of Light Bulbs in the house:				
4-5	-7.407	9.850	-8.226	9.983
	(12.953)	(9.500)	(12.346)	(8.133)
6-7	12.484	14.786	12.157	14.994
	(8.319)	(6.276)	(11.490)	(8.468)
8-9	11.169	5.022	12.032	4.602

Continued on next page

Table 1.4 – *continued*

Variable	OLS Morning Shift	OLS Afternoon Shift	Heckman Estimation Morning Shift	Heckman Estimation Afternoon Shift
	(6.790)	(5.773)	(11.831)	(8.381)
10-15	26.491**	24.693**	28.079**	23.718**
	(5.889)	(5.728)	(11.960)	(9.729)
16-25	8.776	32.522***	10.087	31.933***
	(7.654)	(8.576)	(12.877)	(12.341)
26 and more	3.927	19.440	7.325	17.277
	(10.481)	(13.710)	(15.499)	(16.920)
Internet	-2.208	-0.211	-0.866	-1.400
	(5.101)	(5.277)	(6.388)	(5.918)
Teacher's Characteristics				
Class Size:				
26-41 students	-10.383*	-20.927***	-13.678**	-18.052**
	(5.939)	(6.820)	(10.417)	(13.205)
16-25 students	-47.995***	-21.916***	-70.935***	-11.652
	(15.361)	(5.555)	(38.366)	(18.464)
15 students and less	-26.324	-39.946**	-34.588	-34.559**
	(25.121)	(14.579)	(27.616)	(26.351)
Experience:				
3-10 years	-38.857*	12.559	-37.159*	12.373
	(20.563)	(10.331)	(32.562)	(11.974)
11-15 years	-38.118*	20.364*	-31.971	18.315
	(8.464)	(7.391)	(34.162)	(14.370)
16 years and more	-35.642	15.238	-31.668	14.140
	(6.883)	(5.999)	(34.159)	(13.647)
Hours of work:				
6-16 hours	8.713	-14.775	16.179	-17.206*
	(17.462)	(9.672)	(26.011)	(11.201)
17-34 hours	7.126	-18.796**	15.385	-21.344**
	(8.099)	(5.834)	(24.217)	(11.508)
35 hours and more	3.505	-13.418	14.378	-18.442*

Continued on next page

Table 1.4 – *continued*

Variable	**OLS** Morning Shift	**OLS** Afternoon Shift	**Heckman Estimation** Morning Shift	**Heckman Estimation** Afternoon Shift
	(5.279)	(4.960)	(25.616)	(12.298)
Age:				
30-39 years	14.932	-5.175	20.949	-8.849
	(12.701)	(8.015)	(27.233)	(12.586)
40-49 years	16.315	4.020	20.853	1.248
	(6.140)	(4.955)	(27.319)	(12.567)
50 and older	17.555	4.636	25.644	-0.558
	(5.659)	(5.766)	(29.594)	(15.498)
Teaching 1 subject	3.916	-2.059	5.664	-3.126
	(6.211)	(5.526)	(9.424)	(7.801)
College degree	0.513	-0.904	1.275	-1.882
	(6.149)	(5.712)	(9.635)	(7.656)
Additional Shift	10.881*	16.214***	14.992**	14.184**
	(5.563)	(5.314)	(10.936)	(8.565)
Has Another Job	-7.829	-7.337	-6.728	-8.895
	(8.285)	(6.970)	(14.808)	(9.100)
School Characteristics				
Violence in vicinity	-12.629**	-1.858	-13.289**	-1.198
	(4.893)	(4.448)	(7.580)	(6.193)
Number of Books:				
100-200	-10.956	16.307*	-4.630	13.676
	(14.940)	(9.044)	(23.745)	(17.378)
200-400	-39.342***	-2.161	-30.921*	-5.306
	(9.120)	(6.929)	(24.173)	(15.588)
400 and more	-15.647	5.895	-7.054	2.712
	(5.522)	(4.539)	(23.104)	(14.670)
Number of Computers:				
10 and less	-10.627	-45.601***	-11.811	-45.306***
	(10.129)	(8.886)	(16.920)	(15.650)
11-30	2.351	-29.533***	2.125	-29.671***

Continued on next page

Table 1.4 – *continued*

Variable	**OLS** Morning Shift	**OLS** Afternoon Shift	**Heckman Estimation** Morning Shift	**Heckman Estimation** Afternoon Shift
	(5.948)	(5.176)	(15.591)	(14.050)
31-50	-11.303	-33.162***	-15.187	-31.512***
	(8.031)	(6.615)	(19.961)	(17.941)
50 and more	19.102	-25.696**	16.688	-24.264**
	(8.160)	(8.816)	(21.564)	(20.708)
Disability Facility	-4.526	-12.180*	-5.291	-11.417
	(6.960)	(6.580)	(11.476)	(11.112)
Sport Facility	3.959	14.091**	4.613	13.654*
	(7.305)	(6.328)	(12.181)	(10.892)
Urban	-11.156	-18.686	-8.576	-18.976
	(15.915)	(11.829)	(33.698)	(18.184)
Inverse Mills Ratio			-23.013	13.756
			(27.239)	(16.993)
Constant	452.462***	723.186***	476.723***	687.201***
	(2.406)	(2.164)	(117.567)	(88.548)
N	1,367	1,212	1,367	1,212
Presudo R^2	0.161	0.183	0.162	0.184

Standard errors in parentheses are bootstrapped and clustered at school level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.5: Regression Results of Average Spanish Test Scores

Variable	OLS Morning Shift	OLS Afternoon Shift	Heckman Estimation Morning Shift	Heckman Estimation Afternoon Shift
Student's Characteristics				
Male	-27.980***	-25.899***	-30.830***	-27.561***
	(4.899)	(4.735)	(5.122)	(5.267)
Student's Age	-12.382**	-13.211***	-20.064***	-17.051***
	(5.152)	(3.339)	(7.703)	(4.528)
BothParents	-0.817	-13.598**	4.452	-10.459*
	(6.443)	(5.457)	(7.981)	(6.636)
Hours of Study:				
1 hour or less	-12.519	16.379	-5.741	20.853
	(21.865)	(14.367)	(22.127)	(16.285)
2 hours	16.962	25.560*	24.878	31.008**
	(5.814)	(5.200)	(21.822)	(16.917)
3 hours	13.787	31.275**	24.594	38.814**
	(6.098)	(6.426)	(22.649)	(17.894)
4 hours and more	28.242	55.800***	43.329*	66.696***
	(8.035)	(10.422)	(24.352)	(21.414)
Hours of Help:				
Less than 1 hour	30.670**	9.343	30.055**	9.018
	(13.215)	(13.427)	(14.472)	(14.491)
1 to 2 hours	17.001	9.906	15.205	8.427
	(6.525)	(6.629)	(13.077)	(13.921)
3 hours and more	6.008	-3.587	2.450	-6.352
	(5.043)	(4.639)	(13.537)	(13.423)
Mother's education:				
1-3 grades	57.466**	17.011	68.337***	19.534
	(25.480)	(13.321)	(24.328)	(13.990)
3-6 grades	65.666**	23.915*	79.879***	28.485**
	(9.967)	(7.246)	(24.460)	(14.454)
7-9 grades	64.528**	11.406	78.548***	15.661

Continued on next page

Table 1.5 – *continued*

Variable	OLS Morning Shift	OLS Afternoon Shift	Heckman Estimation Morning Shift	Heckman Estimation Afternoon Shift
	(7.021)	(5.569)	(24.256)	(13.986)
10-12 grades	75.244***	27.990*	93.920***	35.852**
	(6.315)	(6.987)	(25.820)	(16.209)
Bachelor Degree	71.972***	30.965*	90.453***	38.438**
	(8.091)	(10.596)	(27.110)	(19.066)
Graduate Degree	43.082	-17.252	57.323*	-13.777
	(13.248)	(15.536)	(27.560)	(23.094)
Father′s education:				
1-3 grades	6.028	-12.590	2.149	-12.704
	(21.415)	(15.205)	(23.946)	(13.376)
3-6 grades	9.152	-17.638	2.982	-19.265
	(10.454)	(8.062)	(25.016)	(13.621)
7-9 grades	13.109	-7.638	9.363	-8.102
	(7.016)	(5.660)	(22.648)	(12.913)
10-12 grades	24.683	-2.711	20.695	-3.665
	(6.218)	(6.082)	(24.044)	(13.871)
Bachelor Degree	45.049*	-1.604	41.807*	-1.170
	(7.637)	(9.995)	(24.678)	(16.505)
Graduate Degree	42.756*	21.447	38.469	20.310
	(10.853)	(14.748)	(26.945)	(24.352)
Mother′s ocupation:				
Elementary occupation	4.605	38.793***	6.104	40.419***
	(11.705)	(9.829)	(10.164)	(9.971)
Worker	-2.666	3.184	-3.981	2.950
	(15.213)	(12.248)	(13.506)	(15.595)
Service employee	17.718	17.348	9.486	13.905
	(16.205)	(10.566)	(15.937)	(10.558)
Service provider	4.081	28.094***	3.216	27.548***
	(8.925)	(9.100)	(9.363)	(8.793)
Clerical support worker	24.112***	17.803	27.301***	20.750*

Continued on next page

Table 1.5 – *continued*

Variable	**OLS** Morning Shift	**OLS** Afternoon Shift	**Heckman Estimation** Morning Shift	**Heckman Estimation** Afternoon Shift
	(8.359)	(10.500)	(8.854)	(12.360)
Associate professional	20.167	16.385	7.558	9.287
	(32.497)	(26.914)	(46.615)	(27.681)
Professional	3.191	9.098	6.568	13.690
	(8.397)	(13.189)	(11.670)	(16.691)
Manager	-37.969	-91.565*	-26.564	-79.671*
	(25.017)	(46.242)	(23.899)	(55.113)
Father′s ocupation:				
Elementary occupation	13.856	25.277**	12.747	26.173**
	(15.869)	(12.404)	(15.538)	(11.571)
Worker	32.853**	39.605***	31.968**	40.472***
	(8.076)	(6.513)	(15.555)	(13.042)
Service employee	18.071	25.522*	18.325	26.841**
	(6.803)	(5.975)	(15.237)	(12.736)
Service provider	25.833	30.515**	27.463*	32.946**
	(7.108)	(7.362)	(15.354)	(13.329)
Clerical support worker	17.377	23.549	20.936	26.706
	(8.967)	(11.178)	(15.652)	(16.733)
Associate professional	-3.874	21.827	-2.428	24.237
	(10.121)	(10.559)	(16.004)	(15.048)
Professional	29.892*	32.922*	34.385*	37.364**
	(6.706)	(9.697)	(16.423)	(20.340)
Manager	-13.790	-25.992	-12.688	-25.448
	(16.297)	(17.206)	(21.090)	(19.229)
Number of Light Bulbs in the house:				
4-5	10.888	8.952	8.983	7.892
	(13.874)	(9.598)	(14.303)	(9.637)
6-7	13.378	17.228*	10.653	15.719
	(8.199)	(6.339)	(13.753)	(9.932)
8-9	15.346	12.272	15.434	12.563

Continued on next page

Table 1.5 – *continued*

	OLS		Heckman Estimation	
Variable	**Morning Shift**	**Afternoon Shift**	**Morning Shift**	**Afternoon Shift**
	(6.538)	(6.092)	(13.445)	(9.688)
10-15	20.320	21.240**	23.410*	23.150**
	(5.577)	(6.044)	(14.316)	(10.890)
16-25	37.074**	30.504**	37.988**	30.785**
	(7.309)	(8.867)	(15.361)	(12.893)
26 and more	28.022	17.533	24.941	15.308
	(11.735)	(12.935)	(18.761)	(16.918)
Internet	-2.061	6.216	0.704	8.164
	(4.920)	(5.703)	(6.037)	(6.903)
Teacher's Characteristics				
Class Size:				
26-41 students	-8.727	-8.085	-18.264**	-16.827
	(5.460)	(7.741)	(10.363)	(15.985)
16-25 students	25.095	-8.005	-23.802	-29.259
	(18.784)	(5.594)	(47.656)	(24.006)
15 students and less	-11.630	-32.049*	-30.769	-43.892**
	(22.728)	(15.493)	(27.018)	(35.285)
Experience:				
3-10 years	12.928	31.291**	11.971	31.550**
	(13.851)	(12.113)	(15.276)	(16.620)
11-15 years	0.087	14.687	0.430	14.961
	(7.704)	(7.714)	(15.734)	(18.759)
16 years and more	21.019	14.435	20.749	15.334
	(6.310)	(5.674)	(14.460)	(17.646)
Hours of work:				
6-16 hours	13.995	14.015	17.101	16.075*
	(11.275)	(8.823)	(14.901)	(11.990)
17-34 hours	3.661	-1.829	8.984	0.977
	(6.881)	(6.072)	(13.971)	(11.651)
35 hours and more	20.425*	12.658	26.863**	17.144*

Continued on next page

Table 1.5 – *continued*

	OLS		Heckman Estimation	
Variable	**Morning Shift**	**Afternoon Shift**	**Morning Shift**	**Afternoon Shift**
	(5.243)	(5.159)	(14.287)	(12.755)
Age:				
30-39 years	2.552	36.277***	1.490	37.647***
	(10.019)	(9.108)	(12.185)	(12.472)
40-49 years	1.607	40.985***	3.491	43.397***
	(5.711)	(5.680)	(13.164)	(13.847)
50 and older	10.207	47.436***	7.463	46.716***
	(5.977)	(5.349)	(14.663)	(14.757)
Teaching 1 subject	5.178	-5.601	8.487	-4.805
	(7.010)	(5.960)	(9.313)	(7.769)
College degree	-10.233	10.716	-4.873	13.353*
	(6.615)	(7.017)	(9.707)	(10.015)
Additional Shift	9.847*	6.138	13.016**	7.510
	(5.395)	(5.177)	(7.777)	(7.026)
Has Another Job	5.701	34.693***	12.398	37.744***
	(11.881)	(7.774)	(16.131)	(12.731)
School Characteristics				
Violence in vicinity	-14.228***	-9.664**	-11.710**	-9.153*
	(4.718)	(4.520)	(7.246)	(5.966)
Number of Books:				
100-200	-10.246	27.593***	2.855	30.054***
	(13.723)	(9.353)	(22.125)	(17.404)
200-400	-35.959***	13.532	-21.538	17.096*
	(8.347)	(7.206)	(21.029)	(14.907)
400 and more	-27.543**	20.051**	-15.179	23.135***
	(5.261)	(4.649)	(19.386)	(13.097)
Number of Computers:				
10 and less	12.779	-5.426	17.222	-2.893
	(9.673)	(8.796)	(15.192)	(14.726)
11-30	9.967	-7.999	13.824	-5.888

Continued on next page

Table 1.5 – *continued*

Variable	OLS Morning Shift	OLS Afternoon Shift	Heckman Estimation Morning Shift	Heckman Estimation Afternoon Shift
	(5.714)	(5.286)	(14.147)	(12.703)
31-50	18.468	-10.864	15.686	-12.586
	(7.424)	(6.858)	(17.351)	(16.083)
50 and more	15.239	29.925**	16.121	31.376**
	(7.666)	(9.093)	(16.648)	(20.252)
Disability Facility	-0.988	13.786*	-4.114	11.180
	(6.568)	(6.635)	(10.746)	(11.242)
Sport Facility	-2.575	-1.999	-4.445	-2.497
	(6.447)	(6.468)	(9.345)	(9.865)
Urban	1.603	-20.842*	12.562	-16.668
	(15.259)	(11.163)	(21.414)	(15.874)
Inverse Mills Ratio			-36.392	-22.970
			(25.232)	(18.939)
Constant	558.869***	547.570***	597.438***	604.146***
	(2.321)	(2.231)	(102.076)	(78.018)
N	1,308	1,224	1,308	1,224
Presudo R^2	0.221	0.231	0.223	0.232

Standard errors in parentheses are bootstrapped and clustered at school level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.6: Decomposition of Expected Math Score Gap

	OLS Estimation		Heckman Estimation	
Total	41.923***		41.923***	
	(2.138)		(2.138)	
Explained	23.732***		35.601**	
	(1.209)		(15.941)	
Student		13.876***		17.874***
		(0.871)		(5.219)
Teacher		9.676***		16.820*
		(0.873)		(10.695)
School		0.180		0.907
		(0.245)		(1.870)
Unexplained	18.191***		2.162	
	(4.870)		(33.220)	
Selection	–		4.160	
	–		(18.481)	

Standard errors in parenthesis. Delta Method is used to get standard errors.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 1.7: Decomposition of Expected Spanish Score Gap

	OLS Estimation		Heckman Estimation	
Total	45.727***		45.727***	
	(2.133)		(2.133)	
Explained	17.553***		38.826**	
	(1.289)		(16.809)	
Student		22.642***		30.683***
		(0.877)		(5.944)
Teacher		-2.801***		9.404
		(1.024)		(11.350)
School		-2.287***		-1.261
		(0.220)		(1.489)
Unexplained	28.174***		-27.427	
	(4.434)		(33.341)	
Selection	–		34.328	
	–		(18.221)	

Standard errors in parenthesis. Delta Method is used to get standard errors.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Chapter 2

GATE TO THE FUTURE: AN ECONOMETRIC ANALYSIS OF THE GIFTED AND TALENTED EDUCATION

2.1. Introduction

Gifted and talented programs have been popular in school districts nationwide. Some public school districts use these programs to retain and attract high achieving students. Another objective of the gifted education is to engage and challenge high-achievement students with the more advanced curriculum. However, this policy may come at a cost since gifted programs require additional funding from already cash-strapped public school districts.

The purpose of this paper is to evaluate the effectiveness of the full-time (self-contained) gifted program versus the part-time (pull-out) program in the Tucson Unified School District. To overcome the challenge of the endogenous nature of the students selection into the programs, I employ two distinct econometric techniques. The motivation behind comparing self-contained versus pull-out gifted program participation is presented below. The first technique is propensity score matching. This method requires the treatment independency assumption conditional on the observed characteristics. Results from my estimation show a positive effect from being in the self-contained gifted program, given the placement scores and other observed students characteristics.

The second econometric approach is the use of the instrumental variable. I instrument for self-contained gifted program participation by the distance between schools attended by the same student, where the current school has the self-contained gifted program and the other is the student's school in the first grade. The instrument is strong and negatively related to the probability of getting into the self-contained program. The results of the main estimation show that there is no statistically significant effect of the self-contained program.

The main conclusion that can be drawn from this analysis is that, on average, the positive effect of the self-contained gifted program may come from the unobserved behavior of the motivated families of the gifted students. However, marginally, there is no statistically significant impact of the self-contained gifted education compared with pull-out program participation. This does not necessarily mean that the gifted program has no effect compared with students which are not in the gifted program at all.

This research is closely related to the well-established line of literature on ability tracking and gifted programs. The main contribution of this study is that after correcting for the selection into the program, I document the positive effect of the unobserved motivational behavior of the student families in the self-contained program.

For the last few years interest in the effectiveness of the gifted programs has been growing, especially through the initiatives of the Jacob Javits Gifted and Talented Educational Act of 1988 and the No Child Left Behind Act of 2002.

The effect of the gifted program on academic performance is inconclusive in the literature. There are a number of studies which find a positive effect of gifted program participation on any academic achievement measure. For instance, Bhatt (2012) finds that participation in gifted programs leads to some positive effects in test score achievement through the instrumental variable approach. Delcourt et al. (2007) compare students in gifted programs to high ability students in districts that do not have gifted programs and find students from gifted programs perform better on achievement tests. Argys et al. (1996) find a small positive net effect of ability grouping on achievement using regional indicators, urbanization indicators and student body characteristics as instruments in a two-stage least square model.

On the other hand, some research shows no effect of the gifted program education on test scores. Bui et al. (2011) use a regression discontinuity design and find no impact of the gifted program on academic performance. Adelson et al. (2011) use propensity score matching estimation and conclude that there is no effect of the gifted programs on academic achievement. Slavin (1987) shows that assigning students to self-contained classes does not enhance student achievement in elementary school.

2.2. Description of GATE Program in TUSD

Tucson Unified School District (TUSD) is the largest school district in Southern Arizona and the second largest district in the state with over 50,000 students in 110 schools. TUSD encompasses approximately 230 square miles that includes much of the city of Tucson as well as rural areas of Pima County and parts of the Pascua Yaqui Indian reservation. The district is heavily minority and very low income.

TUSD adopted the GATE (Gifted and Talented Education) program in 1988. GATE services include both part-time (pull-out) and full-time (self-contained) programs in second through eighth grades. Self-contained programs are administrated in four elementary schools in different areas of the district, one of which is for Spanish dominant and bilingual students. Theoretically, students in special schools have the benefit of full-time instruction at a more advanced pace with a more thorough coverage of content. The teachers in the self-contained program are certified and endorsed in gifted education. The GATE/PLUS or pull-out program is a part-time program available at all TUSD elementary and middle schools. Students in pull-out programs are in a regular classroom for most instructional purposes but leave the regular classroom environment for a portion of the school week to attend special classes with other identified gifted students. In TUSD, students in self-contained classes participate in their program 5 days a week, while part-timers are pulled out of their classes for one and half hours per week.

Students starting from kindergarten can be identified as gifted from the results of cognitive ability tests, which usually take place in all elementary and middle schools in January and early February. In order to be able to take this test, a student should be referred early in the fall semester. Referrals for evaluation for gifted education programs usually originate from teachers. Teachers′ recommendations are based solely on students′ performance in the classroom. Parents may also initiate the request to test their children. Students′ parents must sign the consent form in order for a student to take the test.

All test results are compiled and rank-ordered by the central GATE office. The special Placement Team reviews all test results and teacher checklists submitted with referrals. Students who score at the 97th percentile or above in any one of three areas – verbal, non-verbal, or quantitative reasoning – are considered eligible for the program.

Students are offered placement in self-contained classes based on their rank order and availability of space in the class within the geographic feeder pattern specific to each school with a self-contained program. Figure 2.1 presents this geographic feeder pattern. The star symbols show locations of schools hosting the self-contained program in TUSD. Each of the other four symbols, diamonds, circles, squares, and balloons, represents an elementary school with the pull-out program. Each type of the symbols shows which elementary school "feeds" students to a specific school with the self-contained program. In other words, gifted students from schools marked as yellow circles would be offered an opportunity to transfer to the school with the self-contained gifted program, marked as a yellow star. Sites of self-contained program and the list of elementary schools that "feed" students to each school with a self-contained program are determined by the governing board of TUSD. Students transferring from their residence schools to the school with the self-contained GATE have access to school bus transportation.

Students who are not offered a seat in the self-contained class due to space availability or decide to decline the placement are offered a placement in GATE/PLUS program at their current school. Pull-out programs are inclusive and accommodate a broader range of student abilities. Students placed in the self-contained GATE program in elementary school are not required to test each year to maintain their placement until their 5th grade year. However, pull-out program students can retake the test if they wish to be considered for self-contained placement.

2.3. Data Description

This paper employs the administrative records of TUSD from the 2007-2008 to 2008-2009 academic years. The dataset contains records of students from TUSD elementary schools.

The data include a student's unique untraceable identification number, ethnicity, gender, attendance, AIMS score, Stanford 9 test score, and participation in free or reduced lunch programs. The Arizona's Instrument to Measure Standards (AIMS) is a standardized test designed to measure student achievement in reading and mathematics for Grades 3 though 8. AIMS is usually administered every year in the Spring. Therefore, the dataset contains information on students from grades 3, 4, and 5. Stanford 9 is a norm-referenced achievement test which compares a student's performance to students in the same grade across the nation who took the test at about the same time in the school year. Usually students in grade 2 take the Stanford 9 in the content areas of reading and mathematics.

Information on student's kindergarten and first grade schools is also included. It was also possible to obtain a sample of students with their GATE placement scores. However, those data are not comprehensive and does not contain placement scores of all students in the gifted program.

Tables 2.1, 2.2, and 2.3 offer a first glance of the data. Specifically, Tables 2.1 and 2.2 are the summary statistics of the student sample with the placement scores, while Table 2.3 provides the summary statistics of the bigger sample of students with Stanford 9 test scores. On average, students from the sample with the placement scores are similar in characteristics with the students from the larger sample. Self-contained and pull-out programs have around 45% girls, about 50% are ethnic minorities, and approximately one-fifth of students are in the lunch program. Students from both GATE programs have a very high attendance rate, around 95%.

Despite the similarities in composition, there is a clear difference in all test scores between self-contained and pull-out gifted program students. The difference in students' placement scores supports the fact that in the selection process, higher ability students are filtered into the self-contained program compared to the pull-out program. As a result of this selection the self-contained students, on average, score higher on Stanford 9 and AIMS tests as well.

The summary statistics from Table 2.2 show a slightly different picture. There is quite a difference in student characteristics from the previously discussed samples and between full- and part-timers. Students from the self-contained program still score higher on AIMS reading test. However, their reading placement scores were, on average, lower than the scores of the pull-out students. One possible explanation is that this particular sample is smaller than the other samples, and that is why it might not be representative of the overall gifted student population.

2.4. Empirical Specification and Results

This study compares academic performance of students from self-contained and pull-out gifted programs. Both of these groups of students are high ability students chosen from the general student population. Therefore, there is less heterogeneity among them compared to students who are not in any GATE programs.[1] Both of these groups receive special curriculum instructions. The only difference is that self-contained students are in the program during the entire school week, while pull-out students are exposed to the gifted education curriculum only once a week. By comparing self-contained to pull-out students I can measure the true effect of the specialized curriculum, given that the variation among students′ types is low. Therefore, any positive effect of the self-contained program will indicate the effectiveness of the gifted education in general.

The academic performance of a student i is a function of the students' charac-

[1]Because of unobserved heterogeneity the available data are not suitable for identifying the effects of the GATE program relative to its absence.

teristics (X_i) and the type of gifted program (T_i) the student is in:

$$S_i = F(X_i, T_i) \tag{2.1}$$

2.4.1. Selection on Observables

The selection process to the self-contained program indicates that placement scores are the dominant criteria of entering the gifted education program. Placement scores are also used to rank order students, which determines the probability of getting into a self-contained GATE hosting school. If one observes the vector of students′ characteristics and the placement scores it can be assumed that students from the self-contained and pull-out programs differ only in the set of these observable characteristics.

I have a relatively small sample of students with placement scores in my dataset. It is reasonable to assume that the unconfoundedness assumption will hold, given the placement scores. In other words, selection (T) into the self-contained versus pull-out gifted programs is assumed independent of academic performance (S), conditional on the observed characteristics of the student (X) and the placement score (N). Formally, the assumption is:

$$T \perp (S(0), S(1)) \mid p(X, N) \tag{2.2}$$

where T takes the value 1 if a student is in the self-contained program with the AIMS score, $S(1)$, and 0 if the student is in the pull-out GATE with the AIMS score, $S(0)$. The vector of student characteristics, X, include gender, ethnic minority, lunch program participation, enrollment in special education indicator variables, and the attendance rate thoughout the academic year, along with grade and year fixed effects.

The probability of selection into the self-contained program:

$$p(x, n) = Pr(T = 1 \mid X = x, N = n) \tag{2.3}$$

is the propensity score which is used to match similar students from two groups.

Since it is possible to observe a student's score from only a single treatment, $S(0)$ or $S(1)$, this technique allows one to obtain the missing potential outcome score for each student (Rosenbaum and Rubin(1983)). In this analysis, the propensity score is estimated using the logit probability model.

The overall average effect of being in the self-contained program can be estimated by either taking the average of the difference between the observed and potential AIMS scores of all students or by differencing the weighted average of the score of two groups of students. In particular, this study employs the nearest neighbor matching (Heckman et. el. (1997)) and inverse-probability weighting estimators (Rosenbaum (1987), Hirano et. al. (2003)).

It is very important for these estimators to satisfy the common support or overlap assumption. The overlap assumption requires that each student has a positive probability of getting into the self-contained program. Formally, this assumption requires that for each student in the sample of the gifted program:

$$0 < Pr(T = 1 \mid X = x, N = n) < 1.$$

Figures 2.2 and 2.3 show graphical presentations of this assumption. In both AIMS and AIMS reading score samples, the densities of the propensity scores have a very wide region of overlapping. Therefore, it is expected that the average effect estimators are valid and consistent.

The results of these estimations are presented in Tables 2.4 and 2.5. On average, students from the self-contained program score about 2 percent higher on the AIMS test than students from the pull-out program. In general, nearest-neighbor and inverse probability weighting estimators show the same magnitude of the effect. Although the nearest-neighbor estimators are not statistically significant, the inverse-probability weighting estimator shows positive and statistically significant results since it is proven to be more efficient than other propensity score estimators.

The self-contained GATE program has a positive effect on AIMS reading scores. All estimators show that self-contained program students on average perform 4-5 percent better on the reading test.

2.4.2. Instrumental Variables

The analysis presented above is performed on a relatively small sample of students. There might be a concern that this sample is not entirely random. Additionally, students who are offered placement into the self-contained program might decline this offer due to unobserved factors. To address this possibility, I attempt to estimate the causal impact of self-contained gifted program participation on student performance using an instrumental variable approach. This method requires an instrument to be correlated with a student's enrollment in the self-contained GATE program but not to appear directly in the main academic performance equation.

The instrumental variable used in the first stage estimation is the distance from the school a student attended the first grade to the self-contained gifted program school within the geographic feeder pattern. For the selection process, students are rank ordered by their placement scores, with the highest ranked students receiving an invitation to transfer to the self-contained school within their geographic feeder pattern. If they don't want to transfer due to the longer commute time or some other reason, these students can still be in the pull-out gifted program. However, if a high-ranked student is already in the school that hosts the self-contained program, it is most likely that he/she would accept the placement in the program. Therefore, the distance between these schools does not affect the academic performance of students, while it influences the decision of students to be in the self-contained program. I expect this instrument to be negatively correlated with the probability of being in the self-contained gifted program.

Arizona school districts have an open enrollment policy which allows students to enroll in schools outside the area of their residency, even in schools in their neighboring districts. Therefore, to control for the motivated parents or students who might enroll in one of the self-contained schools beforehand, I include an additional indicator variable for enrollment outside the area of residency.

Formally, the performance of students on math or reading AIMS (S) depends on the students' characteristics (X):

$$S_i = \beta_0 + \beta_1 X_i + \beta_2 T_i + \epsilon_i \tag{2.4}$$

where the vector X includes gender, ethnic minority, lunch program participation, enrollment in special education indicator variables, attendance rate thoughout the academic year, and grade and year fixed effects. It also includes the Stanford 9 mathematics or reading test scores to control for the unobserved ability of students. The variable of interest, T, is endogenous in this equation. So I use the instrument M, the distance from the first grade school to the self-contained gifted program school within its geographic feeder pattern, which determines the probability of a student getting into the self-contained program:

$$T_i = \gamma_0 + \gamma_1 M_i + \beta_2 X_i + u_i \tag{2.5}$$

Tables 2.6 and 2.7 present the results of the instrumental variable model estimation. The first stage estimation shows that the distance between the first grade school and the assigned school with the self-contained gifted program is negative and statistically significant. This indicates that the further the first grade school is from the self-contained program school the less likely a student would transfer to the school with the self-contained program given that she/he scored relatively high on the placement test.

The IV estimate shows that enrollment in the self-contained gifted program has no statistically significant effect on the AIMS test score. Although the second stage estimation results are positive for both math and reading AIMS scores, the standard errors are too big to conclude that students benefit from being in the self-contained program in comparison with the students in the pull-out gifted program.

The difference in the results between the two econometric models can be explained by the design of the estimators. The propensity score matching estimators give the overall effect of the self-contained program, while the instrumental variable method identifies the local average effect. In other words, the instrumental variable approach captures the difference in the AIMS scores of students whose transfer decisions were affected by the distance between their first grade school and the self-contained school. Highly motivated parents who wanted their children to be in the self-contained gifted program might not be affected by the distance and the commute time. On the other hand, there are parents who do not care about the self-contained gifted program at all. They would not transfer their children to the self-contained GATE school no matter how close it is. Hence, the distance instrument does not include the students' academic performance in the estimation of the average effect of the self-contained program. It is reasonable to believe that students from highly motivated families are getting more out of the gifted programs and their academic success might not be solely driven by the curriculum of the GATE program. The positive effect that we observe through the propensity score matching model estimations could come from the extra support and encouragement from parents as well as additional help from outside of school.

Another possible explanation of the difference in the estimates from the two different econometric specifications is that the sample of students with the placement scores is systematically different from the more comprehensive sample without the placement scores. To check if this explanation is plausible, I perform the estimation using the distance instrumental variable on the sample with the placement scores.

The results of this estimation is in the Tables 2.8 and 2.9. The instrumental variable is still statistically significant and negative in the first stage of the estimation. The effect of the self-contained gifted program on the AIMS test performance is positive but not statistically significant which is the same as the results from the large sample estimation. However, there is a positive and statistically significant effect, 0.352 points which approximately translates to 1.4 percent, on the reading AIMS score. A possible explanation for this is that this particular sample of self-contained gifted program students was chosen from the upper part of the student distribution while pull-out program students are from the lower part. However, in general, I think that the results of the instrumental variable estimation performed on the small sample still support the story of the students from motivated families.

2.5. Conclusion

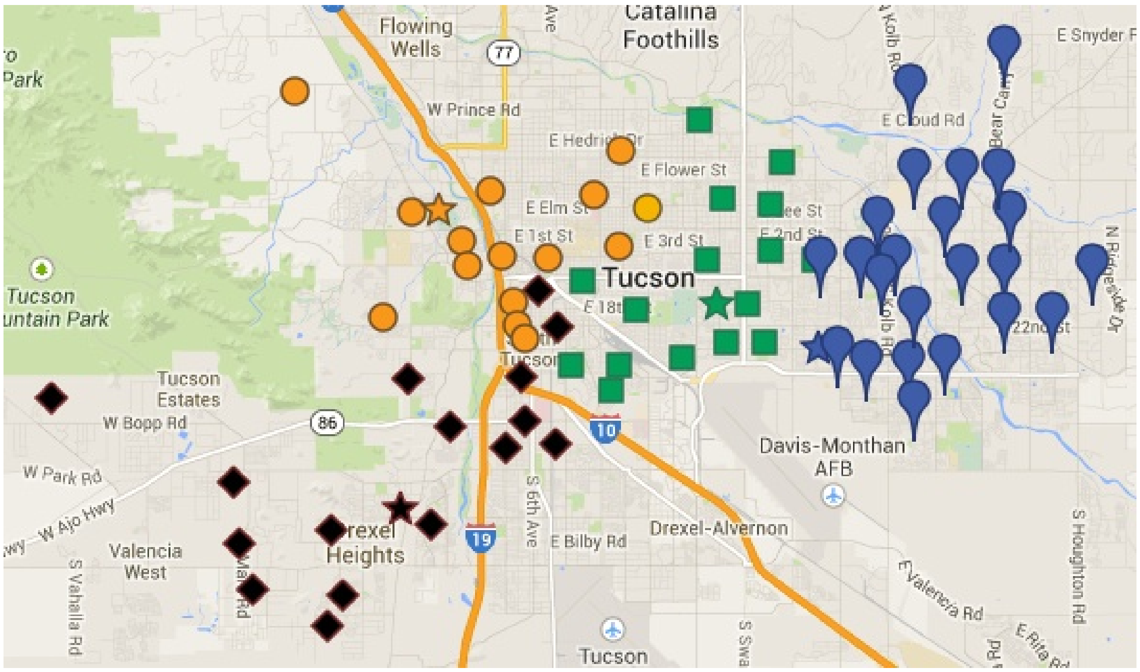
In conclusion, this study seeks to identify the impact of the self-contained gifted program on student academic performance. The unique setting of gifted education in the TUSD provides an opportunity to consider how ability grouping affects students at the upper tail of the ability spectrum. Previous empirical research could not unanimously conclude that the gifted programs have any positive effects on the academic achievements of students. In addition, the endogenous assignment of students into gifted programs makes such analysis challenging.

I estimate the effect of the self-contained program on the results of the standardized tests. This paper uses both propensity score matching and instrumental variables to estimate the causal effect of the self-contained GATE program. While the propensity score matching estimates suggest that students may get higher scores on the AIMS test by being in the self-contained program, instrumenting for the assignment into the self-contained program shows that there is no effect. This difference in the two sets of results may be explained by the fact that this positive effect of the self-contained gifted program could be driven by the unobserved motivational behavior of gifted students beyond the program curriculum.

Overall, this analysis highlights the need for more research on the effect of the motivational behavior of the families of the gifted students. Further research of these factors can be informative for organizing and structuring gifted programs.

2.6. Tables and Graphs

Figure 2.1: Self-Contained Schools Geographical Feeder Pattern[2]



☆ indicates the location of self-contained schools
Four other symbols show geographic feeder pattern specific to each self-contained school

[2]The map was created using Google Maps

Table 2.1: Summary Statistics of Students with Placement Scores:
AIMS sample

Variable	**Self-Contained**		**Pull-Out**		**Difference**	**t-value**
	Mean	**Std. Dev.**	**Mean**	**Std. Dev.**		
AIMS	90.525	7.980	87.603	10.255	2.921***	2.772
Female	0.441	0.499	0.445	0.498	-0.004	0.067
Ethnic Minority	0.477	0.502	0.527	0.500	-0.049	0.918
Lunch Program	0.270	0.446	0.217	0.413	0.053	1.169
Special Education	0.027	0.163	0.038	0.192	-0.011	0.566
Attendance	96.084	3.552	95.934	3.445	0.150	0.402
Placement Score	76.441	24.835	62.803	27.456	13.638***	4.714
N	111		391			

Table 2.2: Summary Statistics of Students with Placement Scores:
AIMS reading sample

Variable	**Self-Contained**		**Pull-Out**		**Difference**	**t-value**
	Mean	**Std. Dev.**	**Mean**	**Std. Dev.**		
AIMS reading	3.404	0.495	3.179	0.541	0.225***	2.859
Female	0.386	0.491	0.426	0.495	-0.040	0.542
Ethnic Minority	0.789	0.411	0.843	0.365	-0.053	0.960
Lunch Program	0.368	0.487	0.306	0.462	0.062	0.900
Special Education	0.053	0.225	0.038	0.192	0.014	0.488
Attendance	95.906	3.396	95.965	3.551	-0.059	0.113
Placement score	90.947	12.822	92.770	8.405	-1.823	1.311
N	57		235			

Table 2.3: Summary Statistics of Students:
Instrumental Variable Sample

Variable	**Self-Contained**		**Pull-Out**		**Difference**	**t-value**
	Mean	**Std. Dev.**	**Mean**	**Std. Dev.**		
AIMS	90.026	7.978	87.249	9.953	2.776***	5.098
AIMS reading	3.482	0.536	3.326	0.519	0.156***	5.268
Female	0.448	0.498	0.478	0.500	-0.030	1.077
Ethnic Minority	0.490	0.501	0.520	0.500	-0.031	1.083
Lunch Program	0.207	0.406	0.222	0.415	-0.015	0.628
Special Education	0.021	0.143	0.040	0.197	-0.019*	1.820
Attendance	95.538	3.635	95.807	3.674	-0.270	1.299
Stanford 9 Math	79.874	16.560	69.368	20.693	10.506***	9.281
Stanford 9 Reading	70.817	17.023	64.527	21.532	6.290***	5.348
N	382		1,711			

Figure 2.2: Overlapping Densities with Placement Scores, AIMS

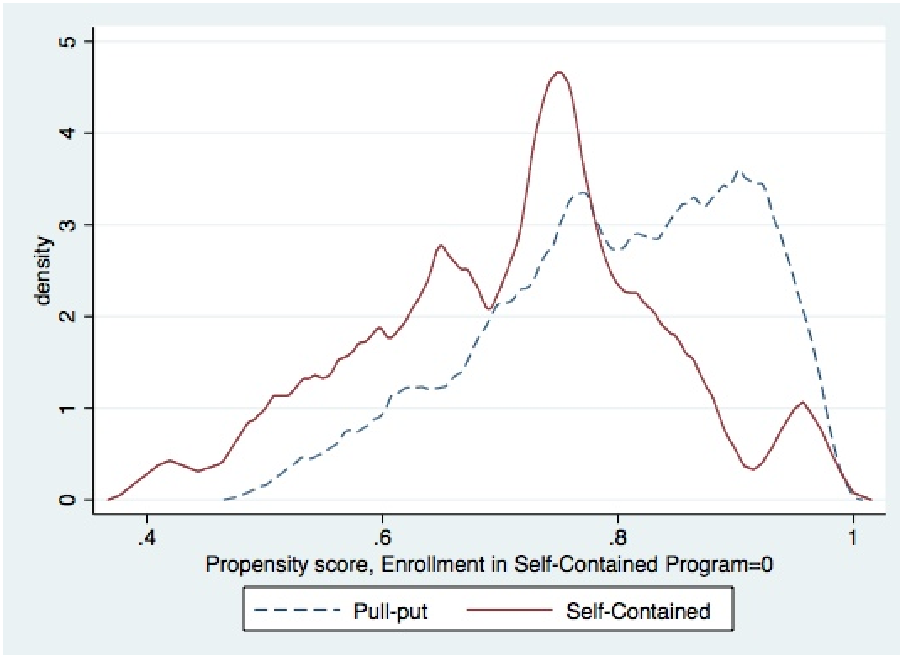


Figure 2.3: Overlapping Densities with Placement Scores, AIMS reading

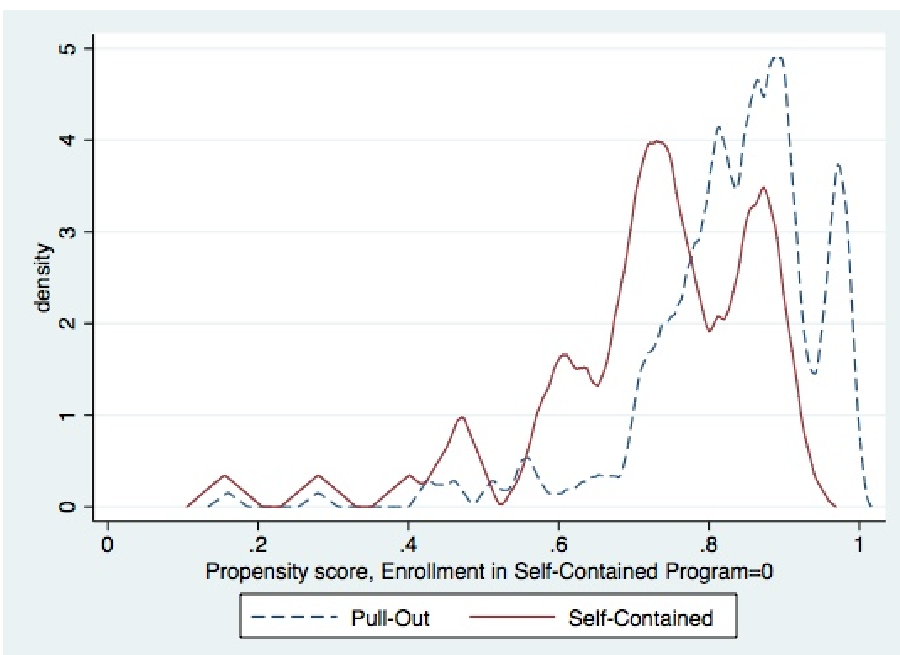


Table 2.4: The ATE of Self-Contained Program, AIMS:
Propensity Score Matching

Estimation Method	Estimate	Standard Error
OLS	1.289	0.888[1]
One nearest neighbor propensity score matching	1.762	1.349[2]
Three nearest neighbor propensity score matching	1.588	1.155[2]
Inverse-probability weights	2.017*	1.128[1]

The specification includes Attendance, Female, Ethnic Minority, Lunch Program, Special Education, grade, and year indicator variables.
Maximum possible AIMS score is 100.
[1] Robust standard errors.
[2] Abadie-Imbens standard errors.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.5: The ATE of Self-Contained Program, AIMS reading:
Propensity Score Matching

Estimation Method	Estimate	Standard Error
OLS	0.238**	0.102[1]
One nearest neighbor propensity score matching	0.154*	0.091[2]
Three nearest neighbor propensity score matching	0.163*	0.084[2]
Inverse-probability weights	0.208***	0.072[1]

The specification includes Attendance, Female, Ethnic Minority, Lunch Program, Special Education, grade, and year indicator variables.
Maximum possible AIMS reading score is 4.
[1] Robust standard errors.
[2] Abadie-Imbens standard errors.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.6: The ATE of Self-Contained Program, AIMS:
Instrumental Variable

Variable	Estimate	Standard Error
OLS		
Self-Contained	1.092	1.229
2SLS		
First stage		
Distance	-0.042***	0.003
Second stage		
Self-Contained	0.220	2.196

The specification includes Attendance, Female, Ethnic Minority, Lunch Program, Special Education, grade, and year indicator variables.
Maximum possible AIMS score is 100.
Standard errors are clustered at the school level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.7: The ATE of Self-Contained Program, AIMS reading:
Instrumental Variable

Variable	Estimate	Standard Error
OLS		
Self-Contained	0.104**	0.047
2SLS		
First stage		
Distance	-0.043***	0.003
Second stage		
Self-Contained	0.039	0.086

The specification includes Attendance, Female, Ethnic Minority, Lunch Program, Special Education, grade, and year indicator variables.
Maximum possible AIMS reading score is 4.
Standard errors are clustered at the school level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.8: The ATE of Self-Contained Program, AIMS:
Instrumental Variable on the Sample with Placement Scores

Variable	Estimate	Standard Error
OLS		
Self-Contained	1.289	0.932
2SLS		
First stage		
Distance	-0.041***	0.006
Second stage		
Self-Contained	3.628	2.516

The specification includes Attendance, Female, Ethnic Minority, Lunch Program, Special Education, grade, and year indicator variables.
Maximum possible AIMS score is 100.
Standard errors are clustered at the school level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.9: The ATE of Self-Contained Program, AIMS reading:
Instrumental Variable on the Sample with Placement Scores

Variable	Estimate	Standard Error
OLS		
Self-Contained	0.238**	0.101
2SLS		
First stage		
Distance	-0.054***	0.009
Second stage		
Self-Contained	0.352**	0.152

The specification includes Attendance, Female, Ethnic Minority, Lunch Program, Special Education, grade, and year indicator variables.
Maximum possible AIMS reading score is 4.
Standard errors are clustered at the school level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Chapter 3

SCHOOL CHOICE UNDER OPEN ENROLLMENT

3.1. Introduction

Budget cuts and declining student enrollment have forced some of the nation's largest school districts to close schools, a disruption that has often interfered with classroom instruction. Some districts are using enrollment losses and building closures as an opportunity to improve student achievement by shifting kids into better schools. Others have even opened new magnet schools, hoping to attract back those students lost to private or charter schools. Many districts face budget deficits and need to take action – such as shutting down schools – to save their districts from financial ruin.

Chicago Public Schools closed 50 schools permanently in the fall 2013 because of low enrollment and poor academic performance.[1] In 2011 the School District of Philadelphia had nearly 70,000 empty classroom seats, mostly due to students moving to charter schools.[2] Now, almost one quarter of all students in Philadelphia area are enrolled in charter schools. Kansas City Public Schools closed 26 schools in 2010. The district, which was designed for 80,000 students, had only 16,800 students enrolled that year (Dawdall (2011)).

This paper examines what characteristics of schools are most valued by students in the school choice decision. Using a unique individual student panel dataset from TUSD, I adopt a conditional logit model to estimate students′ revealed preferences. In particular, students who enrolled in the schools outside of their neighborhood

[1]Source: CPS press release, May 22, 2013
[2]Source: Philly.com, January 20, 2011

school will identify the characteristics of schools necessary for attracting these students. Knowledge of factors that drive school choice will help school administrators improve the quality and efficiency of their schools while keeping their current enrollment and attracting mobile students.

In spring of 2010, Tucson Unified School District (TUSD) closed 9 schools. This action helped to cut costs and to return approximately $30,000 to every school that remained open. However, because of declining enrollment, further budget cuts, and lack of success in attracting families, the Governing Board of TUSD has approved the closing of an additional 11 schools for the 2013-2014 school year including four middle schools. TUSD comprises about 100 schools and has 13,000 empty seats throughout the district. This number of empty seats translates to approximately 26 empty elementary schools. According to the TUSD's former superintendent, John Pedicone, TUSD has experienced a drop in enrollment in the last five years, of about 2,000 students each year.

Students leaving TUSD choose private or charter schools. According to the National Alliance for Public Charter Schools, 18% of the total student population of TUSD is enrolled in charter schools. Arizona′s open enrollment law, which gives students a choice of schools other than a school in the district of their residence, does not work in favor of TUSD either. Students are opting out to better performing schools in the Catalina Foothills, Vail, Tanque Verde, and Marana districts.

My analysis shows that mobile students are more likely to choose big schools in the wealthier neighborhoods, which has low mobility rates and higher average test scores. Schools in poorer areas and with a high percentage of minorities do not have decreasing enrollment. Students in these schools are less mobile and, therefore, less likely to opt out to a school outside their area of residence.

The problem of school choice under an open enrollment policy has attracted the attention of a number of researchers. Cullen, Jacob, and Levitt (2005) explore the impact of school choice through open enrollment within the Chicago public schools. Their findings suggest that school choice leads to increased sorting by ability: high ability students are more likely to opt-out to better schools and more likely to graduate. In another work, Cullen, Jacob, and Levitt (2006) use the same dataset to estimate the causal impact on student outcomes of gaining access to sought-after public schools. They observe no systematic evidence of benefits to lottery winners on graduation rates, test scores, and school attendance. Ozek (2009) analyzes the impact of intra-district school choice on the academic performance of students in Pinellas County Schools, Florida. The author finds no significant benefit on student achievement from opting out of the assigned public school, although the school choice program leads to significant changes in the frequency of exercising alternative public schooling options and in the composition of the students who choose to transfer out.

Koedel, Betts, Lorien, and Zau (2010) evaluate the integrating and segregating effect of school choice in the San Diego Unified School District. They estimate that the social cost of student segregation in the district is roughly 10 million dollars per year. In his study, Reback (2008) examines parents′ demand for a public school outside their residential school district under the Minnesota Open Enrollment program. He finds that average test scores and socio-economic characteristic are significant predictors of transfer demand.

This paper adds to the academic debate on the direct investigation of school-choice preferences. Hastings, Kane, and Staiger (2005) use a mixed-logit demand model to reveal parents′ preferences for school characteristics in the Charlotte-Mecklenburg School District. They find that parents highly value the proximity of the school to their home. Moreover, preferences for school test scores increase with student income and own academic ability. Burgess, Greaces, Vignoles, and Wilson (2010) estimate the parental demand for academic performance. Using a combined dataset from England, they model the choices made in terms of the characteristics of schools and families and the distances involved. Their findings suggest that the most important factors to families are academic attainment, school socio-economic composition and travel distance. They also show that the distribution of preferences does not vary greatly between different socio-economic groups; in fact, the distribution of preferences of the rich and poor almost completely overlap.

3.2. Institutional Detail and Data Description

Tucson Unified School District (TUSD) is the largest school district in Southern Arizona and the second largest district in the state with over 50,000 students in 100 schools. TUSD encompasses approximately 230 square miles that include much of the city of Tucson as well as rural areas of Pima County and parts of the Pascua Yaqui Indian reservation.

Under the open enrollment program, all students receive preference in attending their residential school district, but they can also apply to any other TUSD school, as well as to schools in neighboring districts without any fee subject to the availability of space. However, public schools in TUSD currently have excess capacity: about 30% of students living within the TUSD boundaries don't attend district schools. Instead, they go to charter schools, private schools or attend classes in neighboring districts under Arizona's open enrollment program. In order to attend a school other than the one assigned, a student must submit an application between the beginning of October and mid-December of the preceding year. Parents of out-of-residence area students are responsible for transporting students to the school of their choice.

This paper employs the administrative records of TUSD from 2007-2008 to 2010-2011 academic years. The dataset contains records of students from elementary, middle, and high schools of TUSD, including magnet schools. The analysis focuses on the choice of middle schools by students. Specifically, I observe the graduates of the elementary school, i. e. 5th graders, making their choice for middle school next year. In the analysis, I use the characteristics of students when they were in the 5th grade. School characteristics are also lagged in order to avoid interdependency of school characteristics on the characteristics of students enrolled in that school. I do not consider high school students since high school choice is likely influenced by factors such as graduation rates and athletic and college preparatory programs that are not central to elementary and middle school choices.

The data include the unique anonymous identification number, race, gender, attendance, AIMS score, school, enrollment in gifted, English learning, and free or reduced lunch programs of a student. Importantly, there is a variable that allows me to identify the group of students who enrolled in schools outside their area of residency. This variable will be denoted as open enrollment status. Table 3.2 gives some idea about the characteristics of students on open enrollment status versus students enrolled at their residency schools. Mobile students, on average, are less likely to be a minority, on the lunch program, or English learners and are more likely to be in the the Gifted and Talented Education Program (GATE). The AIMS score for mobile students is higher on average than students who go to their assigned schools. However, the AIMS score is not reported in this table and not used in the main estimation since about half of students did not take the AIMS test in the spring semester and its value is missing in this dataset.

In addition, the data contain some school characteristics, like the mean of the AIMS score, mobility rate, magnet status, and number of public and charter middle schools in proximity.[3] Considering the large area of TUSD, the middle schools are very heterogenous in their characteristics. The mobility rate is 30% on average and fluctuates between 5 and 55 percent. The district is heavily minority and very low income. About 75% of TUSD's total student enrollment are minorities, more than half of whom are Hispanic. On average, more than 70% of students are enrolled in reduced or free lunch programs.

3.3. The Econometric Specification

3.3.1. Probability of Opting-Out

As a first approach, I model a student′s decision on whether he/she wants to stay in the residential school or whether he/she chooses to go to the different school in TUSD. Given a standard random utility model, let U_{io} represent the expected utility of a student i from choosing a school outside the area of residence and U_{ir} be the expected utility from staying in the local school. Under utility maximization,

[3]The definition of variables are given in Table 3.1

this student will opt-out if

$$U_{io} > U_{ir}.$$

The student's utility from choosing the school on open enrollment, o, is

$$U_{io} = \delta' x_{io} + \eta_{io} \tag{3.1}$$

where δ represents the weight student i places on the components of utility from the school other than the neighborhood school, and x represents the observable student characteristics, such as income, race, gender, etc. The utility from staying in the area of residence is:

$$U_{ir} = \delta' x_{ir} + \eta_{ir} \tag{3.2}$$

Assuming that η_{io} and η_{ir} are independently, identically distributed extreme value, the difference between these two variables is the logistic distribution. So, the probability of opting-out is

$$P_{io} = Pr(U_{io} > U_{ir}) = \frac{exp(\delta' x_{io})}{1 + exp(\delta' x_{io})} \tag{3.3}$$

3.3.2. TUSD School Choice

The model of school choice is also based on a standard random utility framework. Let U_{ij} represent the expected utility of a student i from attending school j out of J alternative schools in TUSD (including the outside option to enroll in any private, charter, or neighboring districts′ schools). Assuming utility maximization, this student chooses the school j if:

$$U_{ij} > U_{ik}$$

$\forall k \neq j$. The student i's utility function can be decomposed into a linear combination of the observed characteristics of the student and the school he/she is attending and the unobserved part ϵ_{ij} which is iid over schools and students (Brownstone and Train (1999)). Specifically, the student's utility from choosing school j is

$$U_{ij} = V_{ij} + \epsilon_{ij} \tag{3.4}$$

The systematic component of the student's utility function is given as:

$$V_{ij} = \beta' x_{ij} \otimes z_j + \gamma_j' m_i s_j + \alpha_j' s_j \tag{3.5}$$

where β represents the weight student i places on academic achievement and other components of utility, x is the vector of observable student characteristics (such as income, race, etc.), and z is the vector of school quality characteristics (such as average test score, racial composition, percentage of school population on lunch program, etc.). Specifically, the model includes the interaction terms of student-specific variables with school-specific characteristics to identify the probability of students valuing certain characteristics of schools. In addition, the outside option variable is interacted with student characteristics in order to see what kind of students are more likely to choose the outside option. The model also has m, the variable indicating the open enrollment status of a student, and s, the fixed effects of middle schools. The interaction of the open enrollment status of a student with the indicator variables for each school will show which schools are more attractive for students who are willing to choose a school outside of boundaries of their residence school. The term $\alpha_j' s_j$ is a constant specific to school j.

ϵ_{ij} contains the effect of unobserved factors on utility, but not included in the components of V_{ij}. In addition, ϵ_{ij} is independently, identically distributed extreme value. The distributional assumption of ϵ allows one to apply the conditional logit model in the estimation of school choice. The conditional logit, unlike a multinomial logit, includes both student-specific and school-specific characteristics in the specification, which is very important in this context. Formally, the probability that student i chooses school k is

$$P_{ik} = \frac{exp(V_{ik})}{\sum_j exp(V_{ij})} \tag{3.6}$$

The choice set includes 25 schools. The alternative and special education schools are dropped out of the set since these schools are not available to the general population of students as a choice. Six schools out of 25 schools are schools that combine primary and middle school in one building. Fifth graders in these schools would be more likely to stay in the same school for the 6th grade. However, other elementary schools' graduates can choose them as their middle schools. In addition, five schools in the choice set are magnet schools.

3.4. Results

Table 3.3 presents the probability that a student is enrolled at a school outside the area of his residence. A mobile student is more likely to be in the gifted program, have higher attendance rate, and is less likely to be minority and in the lunch program. These results show that students from poor neighborhoods with a high percentage of hispanic or other minority population value the benefit of having school transportation services. The costs associated with getting to a school outside the residential school district are too high for them. Therefore, they are more likely to be enrolled in the assigned area school.

The main results are presented in Table 3.4. Students on the lunch program are more likely to choose schools with a high percentage of students on the lunch program, non- English speaking students, and high mobility rate. These findings are consistent with the idea that students from low income families are less mobile and more likely to stay at schools assigned in their areas of residence.

It is not surprising that minority students are more likely to choose schools with a higher percentage of minority students and are less likely to choose schools with higher test scores. These students are also choosing schools with a low percentage of students on a lunch program or an outside option. The set of these results might indicate that for minority, mostly hispanic, students it is very important to be at school with a high concentration of hispanic students even if it means choosing a school other than assigned.

Students with a higher attendance rate choose schools with a lower percentage of minority students and higher test score. These students are less likely to leave TUSD. Magnet schools will attract them. Magnet schools also attract students on the lunch program. This shows that students from low-income families but highly motivated might stay in the district if they are offered a special academic program.

However, the interaction term of the student's minority variable with the magnet school do not show any statistical significance. This suggests that magnet schools do not have any effect in the school choice decision of the minority student population as well as the non-minority.

Schools with other public and charter schools within the vicinity of 3 miles attract students with higher attendance rates and students not on the free or reduced lunch. It can be interpreted as evidence that schools facing competition from nearby public and charter schools are able to bring in motivated students and less likely to lose general enrollment.

The other set of results I would like to discuss is the interaction terms of outside choice with the year indicators. There is a clear pattern of students leaving the public schools of TUSD. One of the possible explanations is that there is a population migration out of Tucson. However, the Census data do not support this. The population of school age children in Tucson, i. e. older than 5 and younger than 17 years old, approximately stayed the same: 85,566 in 2000 and 84,688 in 2010. Meanwhile, enrollment has risen in charter schools, and enrollment in private schools is also climbing. For instance, in Tucson, enrollment in Catholic elementary and high schools has grown by 9.6 percent, from 4,788 students to 5,250, since the 2003-04 school year, according to the Catholic Tuition Support Organization. Interdistrict open enrollment policy allows students to choose schools in the neighboring school districts. This works against schools in TUSD. The enrollment in the neighboring

Catalina Foothills School District, for example, was also steadily increasing: from 4,700 in 2008 to 5,000 in 2010. Therefore, it is logical to assume that there is a growing trend of students choosing charter, private, or neighboring district schools.

The results of the interaction term of the open enrollment with school dummy variables are in the last part of the Table 3.4. These results suggest that 11 schools are the most popular schools among students who are willing to choose a school outside their area of residency. In order to see what observable characteristics of these schools contributed to the students′ choice, schools are grouped into two categories based on the statistical significance of the open enrollment and school dummies interaction term. Table 3.5 presents the summary statistics of the school regrouping.

Statistically significant schools, in comparison with other schools, on average have fewer minority students and students enrolled in free or reduced lunch and English learning program. These schools′ mobility rates are lower and average AIMS scores are higher. Students tend to choose bigger schools: on average sixth grade enrollment of schools chosen by open enrollment students is higher by about 200 students. These schools are not magnet or K-8 schools. Another interesting feature is that there are more charter schools within a 3 mile radius. This confirms the finding above that students prefer schools that can compete with other public and charter schools.

3.5. Conclusion

Many public school districts have lost general student population due to the growing popularity of charter schools and open enrollment policy. Tucson Unified School District had to close down schools throughout the district due to the low student enrollment in the past few years. Currently TUSD started an advertising campaign over the radio and TV to attract more students into the district. This paper tries to understand the determinants of the student school choice.

Using the detailed administrative dataset, I analyze the student school choice in TUSD. The identifying variable of student's open enrollment status and various school characteristics show that students choose big schools with higher average AIMS scores and lower mobility rates.

Many public schools try to hold on to the student population by offering them magnet schools. My findings show that low income students with high attendance rate might stay in the district if given the option of attending a magnet school, although results also suggest that minority students are less likely to be attracted by the magnet status of a school.

The panel dataset allows me to identify the group of students choosing the outside option: charter schools and public schools in the neighboring school districts. There is a growing tendency of students leaving TUSD. Low income students are less likely to opt out from TUSD. However, the results suggest that popular public schools win the competition with charter schools.

3.6. Tables and Graphs

Table 3.1: Definitions of Variables

Variable	**Definition**
Student Variables	
Male	Indicator variable for a male student
Ethnic Minority	Indicator if a student's ethnicity is hispanic, african american, or native american
Lunch Program	Indicator if a student receives free or reduced lunch
English Learner	Indicator if a student is English language learner
GATE	Indicator if a student is in the gifted and talented program
Attendance	Average attendance rate throughout the academic year
School Variables	
% of Ethnic Minority	Percentage of ethnic minority school population
% of Students on Lunch Program	Percentage of school population receiving free or reduced lunch
% of English Learners	Percentage of English learning school population
Mobility Rate	A measure of how many students are transferring in and out of a school $\frac{(\text{Entries after 1st Day} + \text{Reentries} + \text{Withdrawals})}{(\text{1st Day Enrollment} + \text{Entries after 1st Day})} * 100$
Mean of AIMS Score	Average of school population AIMS score
6th Grade Enrollment	Total number of students in 6th grade
Magnet Status	Indicator if a school has any magnet status
K-8 School Status	Indicator if a school enrolls students from kindergarten through 8th grade
# of Public Schools within 3 Miles	Number of public schools in the radius of 3 miles
# of Charter Schools within 3 Miles	Number of charter schools in the radius of 3 miles

Table 3.2: Summary Statistics of Students

	All Students	**Students Enrolled Outside Their Area of Residency**	**Students Enrolled In Their Area of Residency**
Male	0.5198	0.5281	0.5194
Minority	0.7078	0.6	0.7132
Lunch Program	0.4488	0.3725	0.4526
English Learner	0.0713	0.0467	0.0725
GATE	0.1474	0.2263	0.1435
Attendance	0.9403	0.9472	0.94
N	17,654	835	16,819

Table 3.3: Probability of Enrollment Outside of Student′s Area of Residency

Students Variable	**Coefficient**	**Robust Std. Error**
Lunch Program	-0.196***	0.0129
Minority	-0.4027***	0.0064
Attendance	2.0499***	0.0817
English Learner	-0.25***	0.0109
Gifted Program	0.4586***	0.0043
Constant	-4.6701***	0.0771
N	17654	
Pseudo R^2	0.0145	
Log-Likelihood	-83,203.62	

Standard errors are clustered at the school level.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.4: Condition Logit Results

Student	School Variable	Coefficient	Std. Error
Lunch	* % of Minority	-0.0015	0.0021
	*% of English learners	0.0160***	0.0039
	*Mobility rate	0.0054*	0.0032
	*Mean of AIMS score	-0.0061	0.0038
	*Outside Option	-1.2160***	0.3171
	*Magnet School	0.1961***	0.0603
	*% on Lunch Program	0.0162***	0.0036
	*K-8 School	-0.1911**	0.0761
	*# of Public Schools within 3 miles	-0.0161**	0.0070
	*# of Charter Schools within 3 miles	0.0042	0.0046
Minority	*% of Minority	0.0592***	0.0026
	*% of English learners	-0.1503	1.8780
	*Mobility rate	-0.0015	0.0040
	*Mean of AIMS score	-0.0087**	0.0044
	*Outside Option	2.1474***	0.3572
	*Magnet School	0.0015	0.0727
	*% on Lunch Program	-0.0151***	0.0041
	*K-8 School	0.1624	0.1217
	*# of Public Schools within 3 miles	-0.0139	0.0095
	*# of Charter Schools within 3 miles	-0.009	0.0057
Attendance	*% of Minority	-0.0328***	0.0047
	*% of English learners	0.6397	1.7383
	*Mobility rate	0.0075*	0.0043
	*Mean of AIMS score	0.0164***	0.0043
	*Outside Option	-3.4852***	0.4744
	*Magnet School	0.7487*	0.4550
	*% on Lunch Program	-0.005	0.0054
	*K-8 School	0.4558	0.5922
	*# of Public Schools within 3 miles	0.1842***	0.0591
	*# of Charter Schools within 3 miles	0.1985***	0.0411
Outside Option*Year2009		0.0246	0.0549

Continued on next page

Table 3.4 – *continued*

Student Variables	School Variables	Coefficient	Std. Error
Outside Option*Year2010		0.1726***	0.0590
Outside Option*Year2011		0.1591**	0.0690
Enrollment Outside the Area of Residency			
	*Drachman	0.1532	0.5969
	*Ford	0.2591	0.5978
	*Jefferson Park	-12.2866	449.5314
	*Miles ELC	2.3001***	0.2076
	*Pueblo Gardens	-1.4103	1.0088
	*Richey	-12.3464	804.6573
	*Dodge	0.4687**	0.1940
	*Carson	-0.0427	0.2259
	*Doolen	0.3607**	0.1769
	*Fickett	0.2647	0.1663
	*Gridley	0.6859***	0.1534
	*Hohokam	-0.1153	0.2403
	*Magee	0.3602**	0.1686
	*Mansfeld	0.4716***	0.1746
	*Maxwell	-0.4792	0.3189
	*Naylor	-0.3884	0.3697
	*Pistor	0.2662*	0.1615
	*Safford	-0.4357	0.2956
	*Secrist	0.3523*	0.1965
	*Townsend	0.0957	0.2398
	*Utterback	-0.3102	0.2219
	*Vail	0.4317***	0.1666
	*Valencia	-0.4172*	0.2303
	*Wakefield	-0.1367	0.2581
	*Roskruge Bilingual	0.4632**	0.2292
Pseudo R^2		0.1591	
Log-Likelihood		-47,945.75	

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

School fixed effects are included in the estimation.

Table 3.5: Summary Statistics of Schools

	Chosen by Mobile Students	**Other Schools**	**Difference in Means**	**T-stat**
% of Minority	58.30	79.32	-21.02***	-5.72
% of Students on Lunch Program	47.80	74.20	-26.39***	-8.09
% of English Learners	4.48	8.82	-4.34***	-3.47
Mobility Rate	26.28	36.35	-10.07***	-3.98
Mean of AIMS Score	63.77	52.29	11.49***	4.31
6th Grade Enrollment	684.58	475.07	209.51***	4.92
Magnet Status	0.10	0.33	-0.23***	-2.75
K-8 school Status	0.00	0.27	-0.27***	-3.78
# of Public Schools within 3 Miles	4.60	5.87	-1.27*	-1.95
# of Charter Schools within 3 Miles	4.20	2.60	1.60**	2.23
N	11	10		

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