Double-Shift Schooling:

Does the Morning Shift Guarantee Better Performance?

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Abstract

Many developing countries have adopted the double-shift schooling system as a way to serve more students using constrained resources. The main purpose of double-shift schooling in Mexico is to achieve universal access to basic education. Students in the morning shift often perform better than students in the afternoon shift. Using unique data from Mexico′s National Institute for Educational Assessment and Evaluation (INEE), I use a Heckman selection model to obtain consistent estimators of factors affecting the academic performance of students. These estimators help to identify the average treatment effect (ATE) of the morning session on math and Spanish scores. Holding students′ characteristics constant, the results show there is no statistically significant effect of being in the morning shift. These results suggest that the non-random assignment of students to the schooling session is the reason for the apperent academic inequality between students from different schooling cohorts.

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I. Introduction

Many developing countries, including India, Brazil, Zimbabwe, Russia, Bulgaria, have adopted the double-shift, or double-session, schooling system. Even within the United States, in the 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. The introduction of double shifts also 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.

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. 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 the 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 wages. However, when schools reach their full capacity and begin to operate in two or three shifts, it is difficult to use the school as a learning community where students can spend longer periods of time and engage in extended sessions or extracurricular activities. In addition, the DSS system creates academic inequality between students from different shifts. That is, students from the morning shift, on average, 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 peer effects.

Teachers have to work and often want to work to improve their salary conditions 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 for some reason 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 only during working hours, teachers must work outside their teaching hours without extra compensation. Teachers perform multiple tasks requiring specialization in areas like educating students, monitoring student performance, and student discipline. 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. In other words, children enrolled in the afternoon session may not achieve the same academic performance as those children enrolled in the morning shift.

Because of the perceived difference in academic performance between the different schooling shifts, goal-oriented parents and students wanting 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 from 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.

Using a unique dataset from Mexico$'$s National Institute for Educational Assessment and Evaluation (INEE: *Instituto Nacional para la Evaluación de la Educación*), this study examines factors influencing academic performance of students from different school shifts. More specifically, the paper focuses on ninth grade students of secondary schools from morning and afternoon shifts and examines the effects of socio-economic and academic variables on students test score performance. The paper identifies the average effect of the morning shift on student performance in comparison with the afternoon.

II. Literature Review

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. In her study, Saucedo Ramos (2005) describes a selection process which intentionally places repeaters and students with discipline problems into the afternoon session. She also 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 that 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 that teacher test scores have a small positive relationship to average student achievement scores, although this effect is larger in secondary schools than in primary schools. Rivkin, Hanushek, and Kain (2005) find that 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 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 that teacher quality, measured by teacher fixed effects, has an important impact on student achievement. In other words, teacher quality may be

important; however, the literature negates the effects of teacher productivity due to extended hours of work.

On the other hand, the literature studying the effect of the class start time on the academic performance shows that later start times increase student performance. Carrel, et al. (2010) use policy changes in the daily schedule of the US Air Force Academy, along with the randomized placement of students and instructors, to show that starting the school day 50 minutes later has a positive effect on the student achievement. Edwards (2012) also supports these results. By analyzing middle school student performance in Wake County, NC over time, he found a two percentile point gain in math test scores for students attending classes later in a day. Cortes, Bricker, and Rohlfs (2012) examine students in Chicago public high schools and find that grades are reduced in first-period classes.

This paper extends the literature by employing a unique INEE dataset to examine whether students in the morning session have an advantage over students in the afternoon school shift. Moreover, this paper extends the educational literature by incorporating the methodology of controlling the selection to two schooling shifts, and correcting for the selection bias.

III. 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 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 was primarily met by double shifting of schools, flexibility of teacher employment practices, and the provision of distance learning models (*telesecundaria*) in lower secondary schools (grades 7–9).

However, enrollment statistics vary by school level. The highest enrollment is in primary schools, followed by lower secondary schools, and still lower enrollment in upper secondary schools. In Mexico, sixty-eight out of every hundred students who enter the first grade complete nine years of basic compulsory education. According to Mexican law, ninth grade

is the last compulsory grade of basic education. After this grade every student faces a choice, to continue on to upper secondary school or to drop out of school. Statistics shows that, on average, only half of ninth-grade graduates choose to stay in school.

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. However, the public school system serves almost 90 percent of all students in the country.

The delivery of basic education in Mexico takes different forms. For instance, 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. In addition, the technical modality trains students in technical skills (e.g., drawing, electronics, auto mechanics) for immediate entry into the labor force. Lastly, the distance learning mode, also known as *telesecundaria*, consists of lectures delivered via satellite TV; the distance secondary schools have one teacher per grade to facilitate lectures, assist students with their schoolwork, and answer questions.

The Ministry of Education of Mexico (SEP: *Secretaría de Educación Pública*) is responsible for the country′s educational system; that includes setting guidelines for teacher salaries, along with the full school calendar year and the length of the school day. Specifically, 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 as four hours, allowing primary schools to operate regular sessions in multiple shifts: morning and afternoon (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, basic 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.

IV. 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 statistics, questionnaires and results of the surveys are available to researchers and the general public. The INEE has collaborated 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 EXCALE project has evaluated random samples of students from different schools of the country: sixth and ninth grades in 2005, third grade in 2006, preschool and sixth grades in 2007, and, finally, ninth grade in 2008.

EXCALE–09 contains 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. EXCALE–09 contains a sample of 11,887 students from 3,304 schools throughout 32 federal states of Mexico. The dataset contains student performance in Spanish (written and reading comprehension), Mathematics, Civic Education and Ethics, and Biology.

The INEE administers paper-and-pencil tests to all ninth-grade students. The test format combines multiple-choice and open-ended questions. 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. This study merges student performance with survey questionnaires,

resulting in a dataset that links each student to her teacher and school.

Most schools in rural areas of Mexico have low enrollment and so do not use multiple shifts. Some children receive their education through *telesecundarias* to make secondary school construction less necessary in a setting with a small number of students. In fact, rural area student performance in reading and math is lower on average in comparison with student performance from urban areas. Similar results are observed in schools with community and indigenous modalities, although the indigenous modality schools use different versions of the national curriculum. In some cases, the community and indigenous classes are consolidated in multi-grade schools where one or two teachers are responsible for teaching all the grades of the primary and lower secondary school. Therefore, all students from rural areas and indigenous schools are dropped from the final dataset to avoid biased results. My final sample includes only students from public schools using general modality, and whose first language and language spoken at home is Spanish.

The merging of the datasets identified matching codes for only math and Spanish reading comprehension scores. Therefore, the compiled dataset for this study includes final math scores of 4,710 students and the final Spanish scores of 4,670 students with 3,029 and 3,041 students in the morning shift, respectively.

Summary statistics are reported in Table 2. 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 students′ and teachers′ variables′ means are different for two cohorts of students. However, it is impossible to reject the hypothesis that the means of schools′ variables are different, which in general supports the use of the same school building for both sessions.

V. Identification Strategy

A. 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. This pa-

per uses two test score equations from morning and afternoon school sessions, along with an equation describing the selection probability of admission into the morning session. 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. Since the probability of admission into the morning session does not completely depend on the decision of the student, the structural model of this probability explains the selection of the exclusion variable in the selection equation.

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 could be students who prefer the afternoon shift, the assumption is close to reality. The fact that on average morning session grades are higher than afternoon grades makes the morning shift more desirable for students. In addition, it is believed that the quality of teaching is better in the morning, because teachers are not yet tired and hence more effective. Therefore, 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

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

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 characteristics, T represents teacher characteristics, and Y represents 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, T, Y, and an error term, v:

$$F_i = f(X_i, T_i, Y_i) + v_i \tag{1}$$

Even though the capacity for both shifts is the same when both shifts use the same schooling facilities, by the school selection process 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 of the constraining capacity of the morning session. In other words, $W = \frac{E_m}{E_a}$ should determine the probability that a student is admitted to the morning session. The sorting function can be modeled as

$$Prob(M_i = 1|X_i, T_i, Y_i, W_i) = \Phi(Z_i'\gamma) \tag{2}$$

where $W_i > 1$, and $Z_i = (X_i, T_i, Y_i, W_i)$.

Given the selection mechanism described above, the sorting equation is the function of gains in shifts$'$ scores and student, teacher, and school characteristics. In other words, the sorting equation is the function explaining a student's probability of being placed in the morning shift. 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

$$M_i^* = \alpha_0 + \alpha_1(S_{mi} - S_{ai}) + Z_i'\alpha_2 - \epsilon_i \tag{3}$$

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

$$S_{mi} = X_{mi}'\beta_{1m} + T_{mi}'\beta_{2m} + Y_{mi}'\beta_{3m} + u_{mi} \tag{4}$$

$$S_{ai} = X_{ai}'\beta_{1a} + T_{ai}'\beta_{2a} + Y_{ai}'\beta_{3a} + u_{ai}, \tag{5}$$

where S_m and S_a are the performance scores for morning and afternoon students. The unobserved terms ϵ is assumed to be a standard normal variable and u_m, u_a are the unobserved

terms with means 0 and variances σ_m^2 and σ_a^2. In addition, the disturbance terms in equations (3), (4), and (5) 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 (4) and (5) into (3) yields a reduced form of the sorting equation:

$$M_i^* = \gamma_0 + Z_i'\gamma_1 - \nu_i \tag{6}$$

where Z is the vectors 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:

$$E(u_{mi}|M_i = 1) = \rho_{u_m\epsilon}\sigma_{u_m}\Big[\frac{-\phi(\psi)}{\Phi(\psi)}\Big] \tag{7}$$

$$E(u_{ai}|M_i = 0) = \rho_{u_a\epsilon}\sigma_{u_a}\Big[\frac{\phi(\psi)}{1-\Phi(\psi)}\Big], \tag{8}$$

where $\rho_u\epsilon$ is the correlation between morning or afternoon respective u and ϵ, σ_u is the standard deviation of the disturbance term of two main score equations, and $\phi(\cdot)$ and $\Phi(\cdot)$ are the standard normal density and cumulative distribution functions, respectively.

B. 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 (6) using all observations from both 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

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

and afternoon shift

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

.

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

$$S_{mi} = X'_{mi}\beta_{1m} + T'_{mi}\beta_{2m} + Y'_{mi}\beta_{3m} + \theta_m\hat{\lambda}_{mi} + \eta_{mi} \tag{9}$$

$$S_{ai} = X'_{ai}\beta_{1a} + T'_{ai}\beta_{2a} + Y'_{ai}\beta_{3a} + \theta_a\hat{\lambda}_{ai} + \eta_{ai} \tag{10}$$

C. Identification of ATE

Heckman's two-stage technique makes it possible to consistently estimate the parameters of the score equations. The unbiased estimators of the score equations can further be used to estimate the conditional ATE. The ATE is the measure of difference in scores between the morning and afternoon shifts,

$$\tau(x) = E[S_{mi} - S_{ai}|X_i, Y_i, T_i] \tag{11}$$

However, considering the fact that, on average, students from the morning shift differ from the afternoon students, the estimate of the ATE is, in some sense, the counterfactual measure of difference of the morning school from the afternoon. In other words, the ATE shows how different the math and Spanish scores of a morning shift student would be from the scores of the same students from the afternoon shift. The popularity of the morning shift among students made the average class size higher in the morning shift. In addition, teachers from the morning shift, on average, are more experienced, work longer hours, and are less likely to teach another shift or have another job. Therefore, in the estimation of the conditional ATE we fix the characteristics of a student and a school but allow teachers′ characteristics to be specific to the shift:

$$\begin{aligned}\tau(x) &= E[S_{mi} - S_{ai}|X_i, Y_i, T_{mi}, T_{ai}] = \\ &= X'_i(\beta_{1m} - \beta_{1a}) + (T'_{mi}\beta_{2m} - T'_{ai}\beta_{2a}) + Y'_i(\beta_{3m} - \beta_{3a})\end{aligned}$$

Then the estimate of the overall ATE would be

$$\hat{\tau} = \sum_{i=0}^{n}\hat{\tau}(x) = \bar{X}'(\hat{\beta}_{1m} - \hat{\beta}_{1a}) + (\bar{T}'_m\hat{\beta}_{2m} - \bar{T}'_a\hat{\beta}_{2a}) + \bar{Y}'(\hat{\beta}_{3m} - \hat{\beta}_{3a}) \tag{12}$$

where $\bar{X}$, $\bar{T}$, and $\bar{Y}$ are the mean vectors of score determining variables including a constant term, and $\hat{\beta}_1$, $\hat{\beta}_2$, and $\hat{\beta}_3$ are the vectors of the estimated returns to the score determinants.

D. Exclusion Restriction and Choice of Variables

Formally, the model is identified with the same set of variables, $Z_i = X_i$, in both estimation stages through the non-linearity of the IMR. However, collinearity is possible between the predicted IMR and the rest of the covariates in the score equations. Therefore, for the model to be identified, at least one excluded variable is required in the first stage estimation of the sorting equation by probit[2] estimation. This excluded variable must be uncorrelated with the academic performance of students in both sessions, but it should affect the probability of getting into the morning shift. The selection model suggests that the main determinant of sorting students into shifts is the ratio of the shift enrollments. 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. Therefore, the variable determining the probability that a student gets into the morning shift is the relative constraining capacity of the morning shift school, $\frac{E_m}{E_a}$.

The enrollment data for each school are available in INEE dataset. Each school of different shifts is assigned a unique, untraceable identification number. In other words, two different shifts sharing the same school building have two different identification numbers. Hence, it is impossible to identify whether two shifts are using the same school building, so relative constraining capacity of the morning shift school, $\frac{E_m}{E_a}$, cannot be constructed, given this data limitation.

Instead, the proxy variable that captures the restrictive relative capacity of a school can be generated using data on shift enrollment and the state the school is in. Specifically, the average state enrollment of the afternoon schools can be used to construct a measure of the constraining capacity of the morning shift in a given state. Similarly, the constraining capacity of the afternoon shift in the state can be calculated using the average state enrollment

[2]The use of the probit model heavily relies on the normality assumption. The graphical and analytical tests, such as Histograms, Skewness/Kurtosist, and Shapiro-Wilk test for normality support the normality hypothesis of the math and Spanish score distributions.

of the morning schools. This proxy variable varies at the school level. Moreover, it captures the differences in the individual state′s limited educational infrastructure and demand for schooling since it varies at the state level. Therefore, the excluded variable determining the probability of getting into the morning shift for students in the morning shift would be constructed as:

$$W_{ism} = \frac{E_{ism}}{\overline{E}_{sa}}$$

where E_{ism} is the student i's morning school enrollment in state s, and $\overline{E}_{sa}$ is the average afternoon enrollment in state s. Similarly, the probability of getting into the morning shift for students in the afternoon would be affected through

$$W_{isa} = \frac{\overline{E}_{sm}}{E_{isa}}$$

where E_{isa} is student i's afternoon school enrollment in state s, and $\overline{E}_{sm}$ is the average morning enrollment in state s.

The excluded variable W for student i captures the enrollment constraint of a student's shift relative to the average state enrollment of the other shift. 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}. Moreover, this excluded variable does 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. The demand for education is determined by the population and the quality of school; there might exist a correlation of enrollment, E, with the test scores, S. In order to control this potential correlation, school quality variables are included in the analysis.

One of the important school variables that are strongly correlated with test scores is class size. For instance, Angrist and Lavy (1999) found that reducing class size induces an increase in test scores for fourth and fifth graders. The research of Card and Krueger (1992) suggests that reductions in the student-teacher ratio for elementary school students caused an increase in test scores on reading and math exams. Hence, school enrollment might be large or small, but possible success in a course strongly depends on the number of students

in a class, or the teacher-student ratio. Other variables determining the school quality, such as the numbers of books and computers in the school and the level of violence in the vicinity of the school, 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 other variables included in the model are student and teacher characteristics. For instance, student characteristics include a student′s gender, age, income, whether she lives with one or both parents, educational level of the student's parents, average number of hours a week the student spends studying outside of school, and whether the student helps around the house. The teacher characteristics include the teachers gender, teaching experience, the total number of hours the teacher works at a given school, 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, and the interaction term between number of work hours and a dummy for another shift. That is, these variables may reveal whether a teacher teaching an additional shift diminishes teacher productivity and, thus, is less effective as a teacher. Also, if a child spends time helping the family it may cause a student to be less effective in the classroom due to fatigue.

Zembar and Blume (2009) show that girls, on average, are better at spelling than boys and perform better on tests involving literacy, writing, and general knowledge, while boys, on average, begin to perform better on mathematics tests in fourth grade. Uwaifo (2008) found significant differences between the academic performances of students from single-parent families and those students from two-parent family structures. Davis-Kean (2005) establishes a relationship between parents′ educational attainment and children′ academic achievement through parents′ educational expectations and parent-specific behaviors. 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.

Dee (2005) identifies a teacher′s gender as an influence on the academic performance of students. Specifically, Dee(2005) shows that same-gender teachers significantly improve the achievement of both girls and boys, along with teacher perception of student performance

and student engagement with the teacher's subject. Card and Krueger (1992) also showed rate of returns to education were higher for individuals from states with better-educated teachers and with a higher fraction of female teachers. Although a number of studies show no strong evidence that a teacher′s experience contributes to a student′s achievement scores; the teacher experience variable is included in this study.

VI. Regression Results

Table 4 presents the OLS estimates of the morning and afternoon score equations, ignoring selection bias. However, the model predicts that without correction for the selective assignment of students into the shifts this parameter would be biased due to endogeneity.

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. As presented in Table 5, the parameter of the chosen excluded variable of relative constraining capacity of the morning school is negative and statistically significant for both mathematics and Spanish scores. It implies that the probability of getting into the morning shift decreases with the increase in the relative enrollment of a school, conditioning on a student and school characteristics. The sign of the excluded variable is the opposite of the model prediction. This fact may be explained by the construction of the excluded variable. The constraining morning school capacity is measured relative to the state average enrollment of the afternoon school, where the state average enrollment may not reflect the true enrollment in the afternoon school. In spite of this, the χ^2 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.

Table 6 reports the estimated score equations with selectivity correction. A number of the estimated coefficients on the variables that explain scores for the difference between two schooling shifts are not statistically significant. That is, a teacher teaching another shift or working an additional job does not affect the performance scores of students in the afternoon shift. Also, a student spending an hour a week helping around the house has no effect on the student's math score in the afternoon shift. However, the estimate of weekly number of hours

a student spent doing his chores is positive and statistically significant in the regression of Spanish scores, implying that one extra hour helping out at home a week increases the average Spanish score by more than 18 points for the morning shift students and by approximately 9 points for the afternoon. The smaller estimated coefficient from the afternoon-shift regression suggests that one hour of work at home increases a student′s Spanish grade by less than it does for a student in the morning shift. This result in some sense supports the hypothesis that reading comprehension abilities weaken later in the day after spending time working in the morning.

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 evidence indicates that boys perform better in mathematics tests while girls perform better on tests of literacy and writing.

The results reveal that the proxy variables for income, the number of light bulbs in a house, and availability of internet access are positive and statistically significant and are consistent with the results of other studies. Moreover, the income coefficients for the morning shift equations are larger than those of the afternoon shift, implying that students with higher family income will perform, on average, better. In general, the estimated coefficients of the remaining variables are not statistically significant.

The number of hours studying for Math is positive and statistically significant, implying that an extra hour of studying a week increases the Math score by approximately 15 points for the morning student and by 10 points for the afternoon student. However, the coefficient for same variable in Spanish regression is negative and statistically insignificant, which may indicate the differences in the level of difficulty of these two courses.

The coefficients of the class size suggest interesting results for the morning shift. On average, one additional student in the morning class increases the average Math score by 2.35 points and the average Spanish score by 1.89 points. Peer effect may be the explanation for the positive results in the bigger class, since the better students are in the morning classes.

Due to the different distribution of students from the two shifts, the estimation of the ATE is implemented using three different ″students″: the average morning student, the average afternoon student, and the average student from the overall distribution. Tables 7 and 8

report the average treatment effect of the morning shift, using the Heckman IMR with equation (12). Even though the results show that students on average would do better in the morning session than in the afternoon, they are 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, in spite of the difference in teachers′ characteristics in different sessions.[3]

The ATE results show 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, that would smooth out any difference between two schooling shift.

VII. Sensitivity Check

One of the caveats of the Heckman two-step estimation is the distributional assumptions. Specifically, the Heckman two-stage estimation model assumes that the term v of the function F and u_m, u_a are jointly normally distributed with zero means and nonzero correlation between v and u_m, v and u_a. Additionally, the distribution of the selection equation error term$v$ is standard normal. This distributional assumption allows one to estimate the parameters of the selection equation using the probit model. In order to check how sensitive the results of the Heckman two-step estimation procedure are, we consider an approximation to the λ. Ideally, it is desirable to estimate γ, the parameters of the selection equation, nonparametrically, or by relaxing the normality assumption. However, due to the large numbers of students′ and schools′ characteristics it is problematic to implement such estimations in practice. So, in the first step, the selection equation is still estimated by probit, but by including second order interaction terms. Then the estimated parameters of the selection equation are used to obtain fitted values of $\hat{\psi}_i$.

In the second stage, the values of $\hat{\psi}_i$ are used to correct selection bias in the score

[3]The two-stage least square estimation using the relative capacity constraint W as an instrumental variable for the shift gives supports the results of the above estimations. The instrument is strong in the first stage, even though the sign is the opposite of the prediction. However, the main regression result shows that there is no effect of being in the morning shift since the coefficient of the shift variable is not statistically significant.

equations. However, in the nonparametric method, instead of, the particular functional form of the IMR used in the Heckman estimation we are using the cubic spline approximation:

$$\hat{\lambda_i} = \alpha_0 + \alpha_1\hat{\psi_i} + \alpha_2\hat{\psi_i}^2 + \alpha_3\hat{\psi_i}^3 + \sum_{k=0}^{K} \alpha_k(\hat{\psi_i} - c_k)_+^3$$

where K is the number of spline knots and c_k is the kth percentile mean of $\hat{\psi_i}$. In the estimation, the value of K used to approximate $\hat{\lambda_i}$ function is 9. The values of c's are the mean of $\hat{\psi_i}$ at 10th, 20th, 30th, 40th, 50th, 60th, 70th, 80th, and 90th percentiles.

Thus, this approximation method allows one to relax the assumption of joint normality of the selection equation error term with the error terms of the score equations.

Tables 9 and 10 show the results of estimation using IMR approximated by cubic spline polynomial. The estimated ATE is not statistically significant. There is no evidence that the morning shift guarantees better scores, holding students$'$ characteristics constant. Moreover, the results of such semi-parametric estimation somewhat repeat the results of the Heckman estimation. So, the Heckman parametric model estimation is not sensitive to the joint normality assumption.

VIII. Conclusion

The double-shift schooling system has been widely used as a mechanism to expand student enrollments and thereby help to achieve the objective of ″Education for All.″ Despite the advantages of this 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; that may lead to a reduction in the quality of teacher instruction. In addition, students$'$ concentration may be lower in the afternoon, which in turn may affect the ability to learn new material and, thereby, result in lower academic performance by students in the afternoon shift.

This study analyzes 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 score gap between students in the morning and in the afternoon shift students. As a result, high ability students are granted admission into the morning shift, while low ability students are assigned to the afternoon session. Therefore, these factors may result in an unequal distribution of educational

opportunities across groups of students.

This study analyzes academic performance of students from different schooling shifts using the two-stage Heckman selection model. Although the effects of the main variables of interest are not statistically significant as predicted, there are interesting statistically significant results on other variables. The average treatment effect of the morning shift supports the finding that there is no statistically significant positive effect of the morning shift holding students′ characteristics constant. The semi-parametric estimation confirms the results of the Heckman two-step estimation model. In other words, the random assignment of students to the different schooling sessions might help to eliminate apparent average difference in scores.

The importance of this research is that it can provide evidence to debate the costs of these types of public policies and, moreover, the ways that government institutions can address the consequences of the double-shift schooling system. In the case of Mexico, double-shift schooling provides a solution to the issue of scarce resources and infrastructure limitations without creating inequalities in the quality of the education students receive between the two sessions.

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X. Tables and Graphs

Table **1**: **Definition of Variables**

Variable	**Definition**
Male	Indicator variable for a male student
AgeStud	Student's age
BothParents	Indicator variable if a student lives with both parents
HrStudy	Hours a student spends studying
HrHelp	Hours a student spends on working or doing house chores
Motheduc	Mother's education
Fatheduc	Father's education
Bulbs	Number of light bulb in student's house
Internet	Indicatior variable if there is an internet access in student's house
ClassSize	Number of students in a group
Experience	Teacher's experience
HoursWork	Hours a teacher works at this school
Work	Indicator variable if a teacher works another shift or has another job
Violence	Indicator variable if there is any violence activity around this school
BooksSchool	Number of books in school's library
CompSchool	Number of computers in school

Table **2**: **Summary Statistics for Math Score Sample**

		Morning Shift		**Afternoon Shift**		**Whole Sample**	
	Variable	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
Students	Male	0.45	0.5	0.49	0.5	0.46	0.5
	AgeStud	15.2	0.53	15.46	0.73	15.29	0.62
	BothParents	0.76	0.43	0.7	0.46	0.74	0.44
	HrStudy	1.99	0.94	1.84	0.95	1.93	0.95
	HrHelp	2.33	1.44	2.42	1.46	2.36	1.45
	Motheduc	12.35	4.12	11.93	4.28	12.2	4.18
	Fatheduc	11.96	4.83	11.24	5.11	11.7	4.94
	LightBulbs	10.04	6.72	8.62	5.8	9.53	6.45
	Internet	0.29	0.45	0.22	0.41	0.26	0.44
Teachers	ClassSize	35.07	6.49	30.88	8	33.57	7.34
	Experience	14.82	5.99	13.97	6.58	14.52	6.22
	HoursWork	29.22	10.75	25.71	11.81	27.97	11.27
	Work	0.62	0.49	0.78	0.41	0.68	0.47
Schools	Violence	0.43	0.5	0.45	0.5	0.44	0.5
	BooksSchool	362.35	158.31	362.08	161.63	362.25	159.49
	CompSchool	19.76	15.2	20.37	15.63	19.98	15.36
	N	3029		1681		4710	

Table **3**: **Summary Statistics for Spanish Score Sample**

		Morning Shift		**Afternoon Shift**		**Whole Sample**	
	Variable	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
Students	Male	0.45	0.5	0.5	0.5	0.46	0.5
	AgeStud	15.22	0.57	15.44	0.71	15.29	0.63
	BothParents	0.77	0.42	0.7	0.46	0.75	0.43
	HrStudy	2.27	0.85	2.17	0.83	2.23	0.84
	HrHelp	1.99	0.95	1.79	0.91	1.92	0.94
	Motheduc	12.41	4.1	12.14	4.49	12.32	4.24
	Fatheduc	11.96	4.86	11.34	4.98	11.74	4.91
	LightBulbs	9.97	6.45	8.71	5.99	9.53	6.32
	Internet	0.29	0.45	0.2	0.4	0.26	0.44
Teachers	ClassSize	35	6.46	30.37	7.45	33.39	7.17
	Experience	14.71	6.19	14.68	6.32	14.7	6.24
	HoursWork	27.89	11.8	23.94	12.02	26.51	12.02
	Work	0.55	0.5	0.74	0.44	0.62	0.49
Schools	Violence	0.45	0.5	0.48	0.5	0.46	0.5
	BooksSchool	359.57	159.23	362.65	160.89	360.64	159.8
	CompSchool	19.59	15.29	20.36	15.77	19.85	15.46
	N	3041		1629		4670	

Table 4: **OLS Regression Results**

		Math Score		Spanish Score	
	Variable	**Morning Shift**	**Afternoon Shift**	**Morning Shift**	**Afternoon Shift**
Students	Male	11.21***	10.26**	-23.96***	-29.46***
		(3.27)	(3.94)	(3.13)	(4.06)
	AgeStud	-25.68***	-17.86***	-22.40***	-13.64***
		(3.07)	(2.67)	(2.75)	(2.86)
	BothParents	-4.50	2.68	-14.13***	-15.41***
		(3.86)	(4.32)	(3.78)	(4.43)
	HrStudy	13.01***	11.16***	-1.45	0.86
		(1.73)	(2.06)	(1.84)	(2.45)
	HrHelp	-1.30	0.00	15.87***	9.82***
		(1.13)	(1.34)	(1.65)	(2.23)
	Motheduc	1.13**	0.54	0.45	0.74
		(0.40)	(0.46)	(0.39)	(0.45)
	Fatheduc	0.74*	0.70	0.41	-0.06
		(0.35)	(0.40)	(0.34)	(0.41)
	LightBulbs	1.78***	1.45***	1.64***	1.22***
		(0.26)	(0.35)	(0.26)	(0.35)
	Internet	10.27**	-1.32	13.20***	8.70
		(3.82)	(4.93)	(3.62)	(5.26)
Teachers	ClassSize	0.85***	1.13***	0.90***	0.48
		(0.26)	(0.25)	(0.25)	(0.27)
	Experience	0.10	0.91**	0.52*	0.47
		(0.28)	(0.31)	(0.27)	(0.33)
	HoursWork	-0.01	-0.06	0.45**	0.37*
		(0.16)	(0.17)	(0.14)	(0.17)
	Work	-0.62	-2.94	7.82*	6.36
		(3.40)	(4.72)	(3.19)	(4.67)
Schools	Violence	-10.19**	-5.05	-7.11*	-12.07**
		(3.28)	(3.89)	(3.12)	(4.01)
	BooksSchool	0.01	0.03*	0.01	0.03**
		(0.01)	(0.01)	(0.01)	(0.01)
	CompSchool	0.35**	0.14	0.08	0.44***
		(0.11)	(0.13)	(0.11)	(0.13)
	Constant	795.02***	648.44***	754.44***	624.45***
		(49.34)	(44.45)	(45.35)	(46.80)
	N	3029	1681	3041	1629
	R^2	0.102	0.099	0.131	0.125

Standard errors in parentheses. Standard errors are clustered at the school level

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table **5**: **Probit Results**

	Variable	Math Score	Spanish Score
Students	Male	-0.05	-0.05
		(0.04)	(0.04)
	AgeStud	-0.33***	-0.27***
		(0.03)	(0.03)
	BothParents	0.10*	0.17***
		(0.05)	(0.05)
	HrStudy	0.06**	0.02
		(0.02)	(0.02)
	HrHelp	-0.03*	0.12***
		(0.01)	(0.02)
	Motheduc	0.01	0.00
		(0.00)	(0.00)
	Fatheduc	0.01	0.00
		(0.00)	(0.00)
	LightBulbs	0.01***	0.01
		(0.00)	(0.00)
	Internet	0.10*	0.21***
		(0.05)	(0.05)
Teachers	ClassSize	0.05***	0.06***
		(0.00)	(0.00)
	Experience	0.01***	-0.00
		(0.00)	(0.00)
	HoursWork	0.01***	0.01***
		(0.00)	(0.00)
	Work	-0.45***	-0.47***
		(0.05)	(0.04)
Schools	Violence	-0.00	0.02
		(0.04)	(0.04)
	BooksSc	-0.00	-0.00
		(0.00)	(0.00)
	CompSc	-0.01***	-0.01***
		(0.00)	(0.00)
	exclude	-0.25***	-0.32***
		(0.02)	(0.03)
	Constant	3.87***	2.81***
		(0.55)	(0.55)
	N	4710	4670
	pseudo R^2	0.146	0.177
	χ^2	896.22	1067.19

Bootstrapped standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table **6**: **Regression Results After Control for Selection**

		Math Score		Spanish Score	
	Variable	**Morning Shift**	**Afternoon Shift**	**Morning Shift**	**Afternoon Shift**
Students	Male	9.67**	11.49*	-24.92***	-29.05***
		(3.51)	(4.50)	(3.19)	(3.59)
	AgeStud	-37.25***	-11.23*	-27.61***	-12.25***
		(5.10)	(5.03)	(4.24)	(3.42)
	BothParents	-0.96	0.90	-10.44**	-16.51***
		(3.82)	(4.72)	(3.83)	(4.51)
	HrStudy	15.04***	9.71***	-1.17	0.86
		(2.08)	(2.24)	(2.11)	(2.43)
	HrHelp	-2.40*	0.54	18.01***	9.14***
		(1.06)	(1.38)	(1.94)	(2.64)
	Motheduc	1.38***	0.42	0.48	0.72
		(0.37)	(0.45)	(0.41)	(0.47)
	Fatheduc	1.01***	0.56	0.48	-0.06
		(0.30)	(0.38)	(0.41)	(0.36)
	LightBulbs	2.17***	1.14**	1.71***	1.16**
		(0.29)	(0.39)	(0.29)	(0.37)
	Internet	12.45**	-3.76	16.37***	7.35
		(4.60)	(5.67)	(4.47)	(5.54)
Schools	ClassSize	2.35***	0.08	1.89***	0.15
		(0.59)	(0.71)	(0.57)	(0.63)
	Experience	0.43	0.59	0.42	0.48
		(0.49)	(0.43)	(0.38)	(0.43)
	HoursWork	0.41	-0.30	0.67**	0.31
		(0.31)	(0.28)	(0.22)	(0.25)
	Work	-16.97	6.89	-1.95	9.04
		(9.07)	(8.71)	(6.68)	(7.03)
Schools	Violence	-10.36*	-5.60	-7.10	-12.20*
		(5.22)	(5.41)	(4.30)	(5.00)
	BooksSc	0.00	0.03	0.00	0.03
		(0.02)	(0.02)	(0.01)	(0.02)
	CompSc	0.06	0.19	-0.12	0.45*
		(0.20)	(0.24)	(0.22)	(0.21)
	IMR1	-73.61*		-42.56	
		(28.86)		(24.01)	
	IMR2		31.98		8.48
			(18.11)		(12.66)
	Constant	870.45***	559.96***	776.67***	607.99***
		(57.58)	(76.17)	(50.43)	(58.27)
	N	3029	1681	3041	1629
	R^2	0.106	0.103	0.133	0.125
	chi2	481.14	147.36	565.38	207.71

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

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table **7**: **ATE for Math Score using Heckman IMR**

Average Morning Student	**Average Afternoon Student**	**Average Student**
14.20	2.75	10.12
(20.42)	(20.96)	(20.57)

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

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table **8**: **ATE for Spanish Score using Heckman IMR**

Average Morning Student	**Average Afternoon Student**	**Average Student**
10.73	3.34	8.15
(16.91)	(16.72)	(16.82)

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

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table **9**: **ATE for Math Score using Approximated IMR**

Average Morning Student	**Average Afternoon Student**	**Average Student**
3.05	-2.79	0.97
(115.83)	(115.76)	(115.80)

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

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table **10**: **ATE for Spanish Score using Approximated IMR**

Average Morning Student	**Average Afternoon Student**	**Average Student**
-96.52	-101.18	-98.15
(111.31)	(111.22)	(111.27)

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

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$