Double Shift Schooling

Quantifying School Value Added

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Overview

Definition

Double-shift schooling (DSS) is an educational policy where one group of students attends school in the morning and a completely different group of students attends in the afternoon, while sharing the same physical infrastructure.

The teaching staff, principals, and administrative personnel may be the same or different. This approach is commonly used in areas where there is a shortage of school resources, such as buildings or teachers, and where it is not feasible to accommodate all students at once.

Research Question

How does the impact of the afternoon shift on student achievement compare with the morning shift?

Why I choose to study Double Shift Schooling

- DSS is a policy undertaken in around 50 developing countries facing budgetary constraints in education supply.[1]
- The effects of DSS on educational achievement, student sorting, enrollment rates, competition, among other topics have not been evaluated in depth.
- In Mexico, around 16% of schools have double shifts, serving close 19% of the total number of students enrolled in primary education.[2]

1

2 The percentages were calculated using the survey 911 of 2012.

Literature Review

To the best of my knowledge the studies that evaluate quantitatively the effects of DSS are presented below.

Cardenas (2009) uses a sample of 11,000 schools and examines the difference in dropouts, repetition rates, and test scores between morning and afternoon shifts and finds that afternoon shifts have lower academic test scores, a higher concentration of poor students and failure rates.

Muñoz Pedroza. mimeo. Examines whether afternoon students experience worst outcomes using a regression discontinuity approach. The author finds that the afternoon shifts increases 12 percent the probability of dropping out of high school. The author exploits a discontinuity in the assignment of students based on their middle schools GPA.

Literature Review

Sagyndykova (2013) applies Heckman's selection model to measure the effects of individual, teacher, and school characteristics on student test scores and estimate the difference in academic performance of students in morning and afternoon school sessions. She finds that the difference in test scores is mainly driven by students characteristics.

Lester and Yasenov (2016) "Double-shift schooling and student success: Quasi-experimental evidence from Europe." Economics Letters 139 (2016): 36-39

Data

1. Student achievement test scores (frequency yearly)
   - I observe the test score of students from 2008 to 2013 for the equivalent to grades K3-K6 in the US education system.
2. School Survey (*Estadística 911*, frequency yearly)
   - *Estadística 911* contains information on school characteristics such as enrollment by grade, number of teachers, number of administrative personnel, class composition (e.g., number of female students), and teachers' characteristics.
3. Georeference database
   - Contains the latitude and longitude and surrounding streets of every school.

Descriptive Statistics

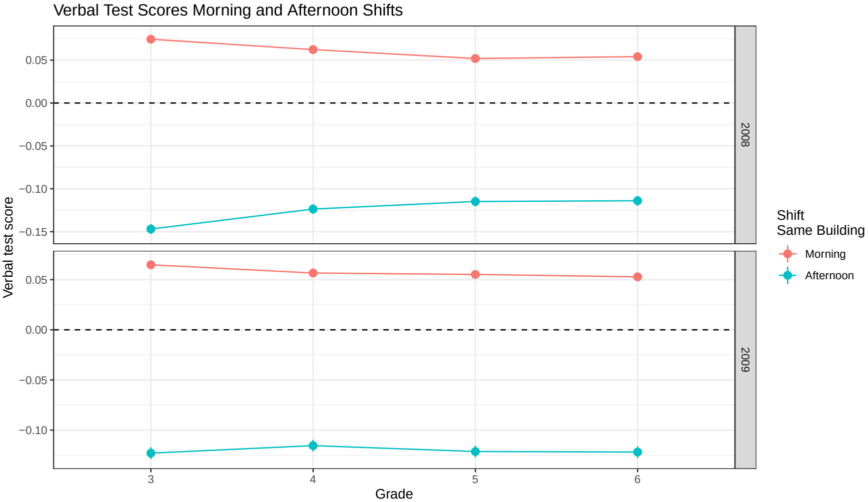
Table: Morning and Afternoon School Differences

year	School Size (# Students)			Group Size			Expenditure by Parents		
	Morning	Afternoon	Difference	Morning	Afternoon	Difference	Morning	Afternoon	Difference
2008	425.9	262.5	163.4	32.7	25.6	7.1	1042.8	894.5	148.3
2009	425.9	260.8	165.1	32.7	25.6	7.1	1152.7	932.1	220.6
2010	424.7	260.3	164.4	32.7	25.7	7.0	1244.9	990.1	254.8
2011	422.9	259.0	163.9	32.5	25.6	6.9	1155.7	975.9	179.8
2012	418.7	254.3	164.4	32.0	25.1	6.9	1184.4	989.2	195.2
2013	414.6	250.4	164.2	31.7	24.9	6.8	1200.0	962.9	237.0

year	Women Ratio			Repeaters		
	Morning	Afternoon	Difference	Morning	Afternoon	Difference
2008	49.3	47.6	1.7	2.7	4.0	-1.3
2009	49.4	47.6	1.8	2.4	3.8	-1.4
2010	49.4	47.6	1.8	2.1	3.4	-1.3
2011	49.4	47.7	1.7	2.0	3.2	-1.2
2012	49.4	47.6	1.8	1.4	2.4	-1.0
2013	49.4	47.6	1.8	0.5	1.0	-0.4

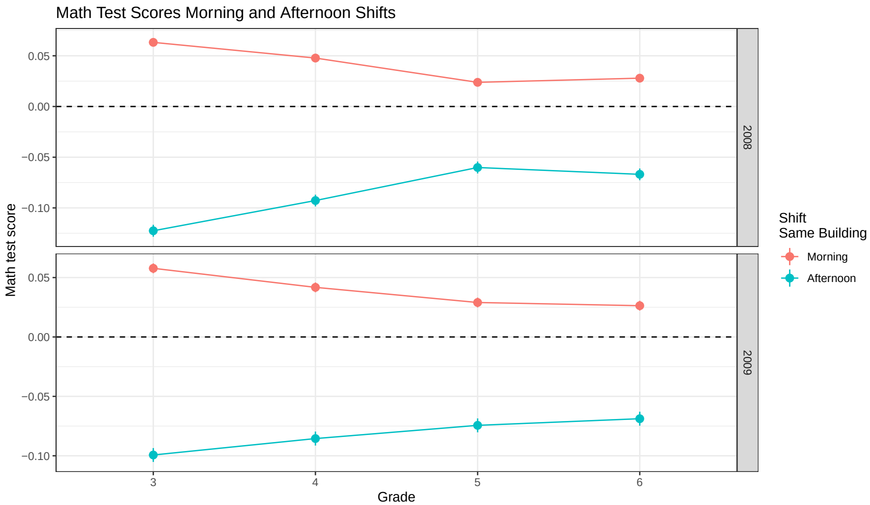
Note: All differences are statistical significant at 1% level.

Achievement



Note: Only matching buildings are included.

Achievement



Note: Only matching buildings are included.

Value Added Model

Sass (2003) and Todd and Wolpin (2003) consider a general cumulative student achievement

$$A_{it} = A_t[F_i(t), S_i(t), \mu_{iO}, \epsilon_{it}]$$

where A_{it} is the achievement level at their t-th year of life. $F_i(t)$ is a vector of family inputs supplied at age t. $S_i(t)$ is a vector of school inputs supplied at age t. μ_{iO} is a composite variable representing individual time invariant characteristics. ϵ_{it} captures measurement errors.

Assuming the cumulative achievement function, $A_t(\cdot)$, does not vary with age and is additively separable. We can write achievement equal to:

$$\begin{aligned} A_{it} = {} & \alpha_1 F_{it} + \alpha_2 F_{it-1} + \ldots + \alpha_t F_{i1} + \\ & + \beta_1 S_{it} + \beta_2 S_{it-1} + \beta_2 S_{it-1} + \ldots + \beta_t S_{i1} + \gamma_t \mu_{iO} + \epsilon_{it} \end{aligned}$$

Value Added Model

Estimating the previous requires data on both current and all prior family inputs. However, I don't have this information. Taking Sass (2003) assumption that family inputs are constant over time and are captured by a student-specific fixed component ϕ_i. However, the marginal effect of these fixed parental inputs on student achievement may vary over time and is represented by κ_t.

This of course implies that the level of inputs selected by families does not vary with the level of school-provided inputs a child receives.

Given the assumptions we have:

$$A_{it} = \beta_1 S_{it} + \beta_2 S_{it-1} + \beta_2 S_{it-1} + \ldots + \beta_t S_{i1} + \kappa_t \phi_i + \gamma_t \mu_{iO} + \epsilon_{it}$$

Value Added Model

The need for data covering the entire school input history can be avoided if one is willing to assume that the marginal impacts of all prior school inputs decline geometrically.

$$A_{it} = \beta_1 S_{it} + \lambda\beta_1 S_{it-1} + \ldots + \lambda^{t-1}\beta_1 S_{i1} + \kappa_t\phi_i + \gamma_t\mu_{iO} + \epsilon_{it}$$

Taking the difference between current achievement and λ times prior achievement yields:

$$\begin{aligned} A_{it} - \lambda A_{it-1} &= \beta_1 S_{it} + \lambda\beta_1 S_{it-1} + \ldots + \lambda^{t-1}\beta_1 S_{i1} + \kappa_t\phi_i + \gamma_t\mu_{iO} + \epsilon_{it} \\ &= \lambda[\beta_1 S_{it-1} + \lambda\beta_1 S_{it-2} + \ldots + \lambda^{t-1}\beta_1 S_{i1} + \kappa_{t-1}\phi_i + \gamma_{t-1}\mu_{iO} + \epsilon_{it-1}] \end{aligned}$$

$$A_{it} = \beta_1 S_{it} + \lambda A_{it-1} + (\kappa_t - \lambda\kappa_{t-1})\phi_i + (\gamma_t - \lambda\gamma_{t-1})\mu_{iO} + \epsilon_{it} - \epsilon_{it-1}$$

Value Added Model

Assuming the impact of parental inputs on achievement, κ_t, and the effect of the initial individual endowment on achievement, γ_t, change at constant rates, then (κ_t - $\lambda\kappa_{t-1}$) and (γ_t - $\lambda\gamma_{t-1}$) can be expressed as constants, κ and γ

$$A_{it} = \beta_1 S_{it} + \lambda A_{it-1} + \nu_i + \eta_{it}$$

Model 2 is a restricted model of model 3

$$A_{it} - A_{it-1} = \Delta A_{it} = \beta_1 \mathbf{S}_{it} + \nu_i + \eta_{it}$$

where $\lambda = 1$

Value Added Model

The valued added model in levels based on Sass (2003) is

$$A_{isbgt} = \rho A_{isbg-1,t-1} + \beta \mathbf{S}_{it} + \gamma Aft_{isbt} + \lambda m_{isbgt} + \theta_i + \epsilon_{isbgt}$$

where A_{isbgt} is the test score of student i in school s in building b in grade g in year t.

$\mathbf{S}_{it}$ is a vector of time varying school characteristics.

A_{isbt} is a dummy variable that captures the effect of the afternoon shift.

m is a dummy variable that takes the value of 0 the year a student changed school and zero otherwise.

θ_i are student fixed effects.

ϵ_{isbgt} is the error.

Dummies

id	year	Afternoon	Change	Morning to Afternoon	Afternoon to Morning	Change to Morning	Change to Afternoon	Test Score
1	2008	0	0	0	0	0	0	-0.3
1	2009	0	0	0	0	0	0	-0.6
1	2010	1	1	1	0	0	1	-0.5
1	2011	1	0	1	0	0	0	-0.3
2	2008	1	0	0	1	0	0	-0.6
2	2009	1	0	0	1	0	0	-0.6
2	2010	0	1	0	0	1	0	-0.6
2	2011	0	0	0	0	0	0	-0.7
3	2008	0	0	0	0	0	0	0.3
3	2009	0	0	0	0	0	0	0.5
3	2010	0	0	0	0	0	0	0.0
3	2011	0	0	0	0	0	0	0.0
4	2008	1	0	0	0	0	0	0.5
4	2009	1	0	0	0	0	0	0.5
4	2010	1	0	0	0	0	0	0.3
4	2011	1	0	0	0	0	0	0.2

Figure: Dummies

Identification Threats

The key identifying assumption is that entry or exit to an afternoon shift is not correlated with other changes in family or student circumstances that affect achievement. The literature has identified potential threats to identification (Hanushek et al. (2002) and Sass (2006)).

- Direct effect of mobility (non-structural moves).
- Temporary drop in student performance and probability of switching.
  - Estimate a logit model.
- Competition. If the opening of an afternoon school raises the level of morning schools.

Grade Dip and Probability of School Change

$$Switched_{ibsgt} = \Delta^2 A_{ibsgt} + \zeta \mathbf{X} + \beta \mathbf{S}$$

where *Switched* takes the value of 1 if a student changed school at year t.

$\Delta^2 A_{isbgt} = \Delta A_{isbgt} - \Delta A_{isbg-1t-1}$ is the change in gains of test scores.

X is a vector of individual students' characteristics (e.g., sex).

S is a vector of school characteristics.

Results

Table: Regression Results Verbal Test Scores

	(1)	(2)	(3)	(4)
Achievement Lag	0.0102**	0.0102**	0.0102**	0.0102**
	(0.0032)	(0.0032)	(0.0032)	(0.0032)
Afternoon	0.0572***	0.0569***		
	(0.0125)	(0.0125)		
Non-struc change		-0.0042		
		(0.0074)		
Afternoon (students entering)			0.0758***	0.1180***
			(0.0178)	(0.0233)
Afternoon (students exiting)			0.0408*	0.0378
			(0.0167)	(0.0209)
Non-struc change (students entering)				-0.0421**
				(0.0151)
Non-struc change (students exiting)				-0.0026
				(0.0124)
Group Size	-0.0057***	-0.0057***	-0.0057***	-0.0057***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Time effects	Yes	Yes	Yes	Yes
Observations	1,248,951	1,248,951	1,248,951	1,248,951
Students	652,034	652,034	652,034	652,034

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

Results

Table: Regression Results Math Test Scores

	(1)	(2)	(3)	(4)
Achievement Lag	0.0570***	0.0570***	0.0570***	0.0569***
	(0.0035)	(0.0035)	(0.0035)	(0.0035)
Afternoon	0.0702***	0.0713***		
	(0.0129)	(0.0129)		
Non-struc change		0.0154*		
		(0.0077)		
Afternoon (students entering)			0.1100***	0.1230***
			(0.0184)	(0.0241)
Afternoon (students exiting)			0.0352*	0.0459*
			(0.0173)	(0.0216)
Non-struc change (students entering)				-0.0130
				(0.0156)
Non-struc change (students exiting)				0.0107
				(0.0128)
Group Size	-0.0052***	-0.0052***	-0.0052***	-0.0052***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Time effects	Yes	Yes	Yes	Yes
Observations	1,248,951	1,248,951	1,248,951	1,248,951
Students	652,034	652,034	652,034	652,034

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

Results Quantiles

Table: Regression Results Quantiles

	(q1)	(q2 and q3)	(q4)
Achievement Lag	0.0423***	0.0502***	0.0436***
	(0.0058)	(0.0038)	(0.0062)
Non-struc change	-0.0077	-0.0143	-0.0290
	(0.0202)	(0.0139)	(0.0182)
Afternoon (students entering)	0.1473***	0.0682*	0.0108
	(0.0412)	(0.0291)	(0.0412)
Afternoon (students exiting)	0.0087	0.0077	0.0856*
	(0.0415)	(0.0277)	(0.0367)
Group Size	-0.0064***	-0.0061***	-0.0035***
	(0.0007)	(0.0005)	(0.0006)
Time effects	Yes	Yes	Yes
Observations	308,910	619,531	308,561
Students	159,940	320,714	159,431

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