Double Shift Schooling in Mexico

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.

Big Policy

- DSS is a policy undertaken in around 50 developing countries facing budgetary constraints in education supply.[1]
- In Mexico, around 16% of schools have double shifts, serving close 19% of the total number of students enrolled in primary education.[2]
- The effects of DSS on educational outcomes have not been evaluated in depth:
  - Students gain or lose achievement by attending an afternoon school?
  - Student sorting affects achievement?
  - It is possible to improve educational outcomes while maintaining the policy (e.g, tracking)?
  - Can school construction increase achievement?

[1] These include Argentina, Bangladesh, Bolivia, Botswana, Brazil, Bulgaria, Burkina Faso, Cambodia, Chile, Colombia, Costa Rica, Democratic Republic of Congo, Dominican Republic, Egypt, Eritrea, Gambia, Ghana, Guinea, Hong Kong, India, Indonesia, Iran, Jamaica, Jordan, Laos, Malaysia, Mozambique, Myanmar, Malawi, Mexico, Namibia, Niger, Palestine, Paraguay, Philippines, Puerto Rico, Romania, Russia, Senegal, Singapore, South Africa, Syria, Trinidad and Tobago, Turkey, Uganda, Uruguay, Thailand, The United States, Zambia, and Zimbabwe.

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

Research Question

How does school value added in afternoon schools in verbal and math test scores compare with morning schools?

Same Building Different Results?

Student Composition

- Afternoon schools serve lower socioeconomic status students Aguirre (2011)
- Principal cream-skimmed students by charging higher fees or making extra requirements (e.g., uniforms, computer lab fees) Zehr (2002)

Teaching Practices

- Parents have the perception that teachers in the afternoon shift are less effective. Zehr (2002) Saucedo (2005) Slater et al. (2007)
- Principals interviewed think teachers in the afternoon shift are less committed Rodríguez (2005)
- There is a higher relation between effort and achievement Aguirre (2011)

School Inputs

- Fewer schools resources Imelda et al. (2007)

Related Literature

- **Methodology** Educational Achievement in Charter Schools Betts (2009) Betting (2005), Bifulco and Ladd (2006) Sass (2006) Hanushek et al. (2002) Arsen and Ni (2012)
- **Double Shift Schooling**: Cardenas (2009) Fabregas (2017) Lester and Yasenov (2016) Muñoz-Pedroza (2016) Sagyndykova (2013)

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- **Double Shift Schooling**: Cardenas (2009) Fabregas (2017) Lester and Yasenov (2016) Muñoz-Pedroza (2016) Sagyndykova (2013)
- **Data Set** Padilla-Romo (2022) De Hoyos et al.(2018) De Hoyos et al. (2021)

Contribution

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Main Findings I find that, on average, children attending the afternoon shift perform **0.06** and **0.07** standard deviations higher for the verbal and math sections than those attending the morning shift.

The result is mainly driven by students in the lower quartile of the distribution entering afternoon schools.

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Plausible Explanations to be explored Tracking Duflo (2011) and Curriculum Matching Pritchett and Beatty (2015

Descriptive Statistics

Table: Descriptive Statistic (year=2010)

Average	Morning	Afternoon	Difference
School Enrollment	425	260	164
Class Size	33	26	7
Expenditure by Parents	1,245	990	255
Women Ratio %	49.4	47.6	1.8
Repeaters %	2.1	3.4	-1.3

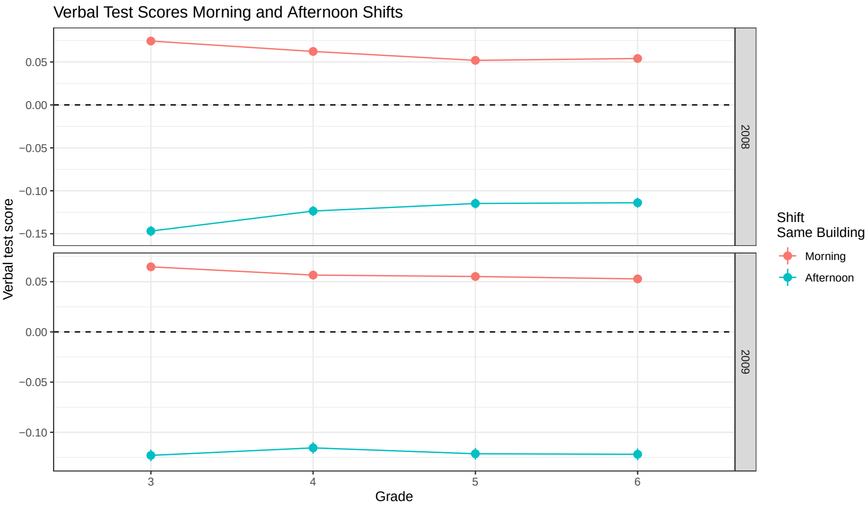
Note: Based on matched schools.
All differences are statistically significant at 1% level.

See details

Data

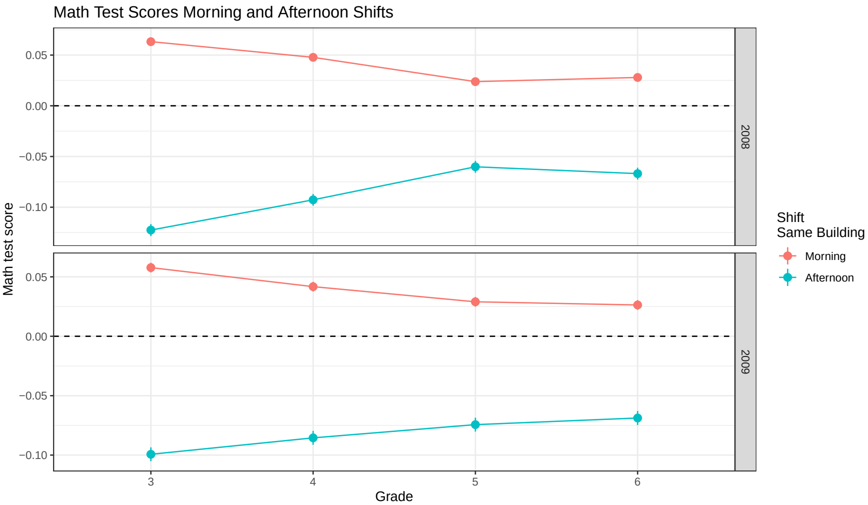
1. Student achievement standardized test scores (frequency yearly)
   - I observe the test score of students from 2008 to 2013 for the equivalent to grades K3-K6 in the US education system.
2. School Survey (*Estadística 911*, frequency yearly)
   - *Estadística 911* contains information on school characteristics 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.

Achievement



Note: Only matching buildings are included.

Achievement



Note: Only matching buildings are included.

Value Added Model

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

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

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.

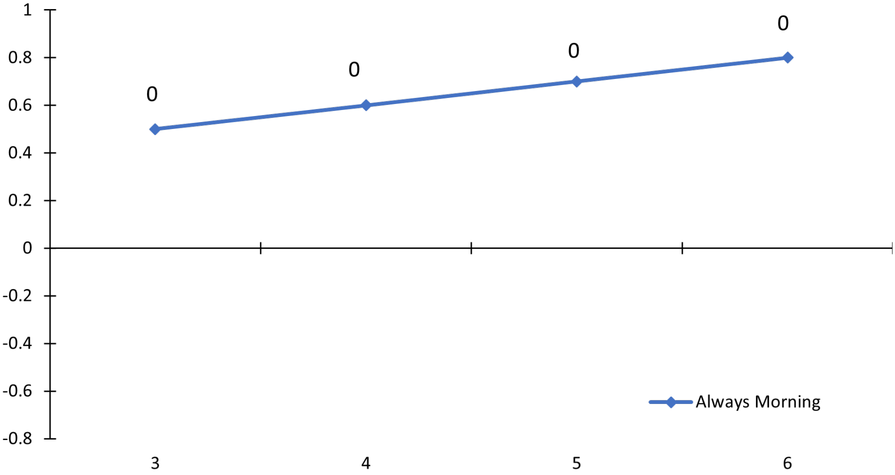
A_{isbt} is a dummy variable that captures the effect of the afternoon shift.

θ_i are student fixed effects.

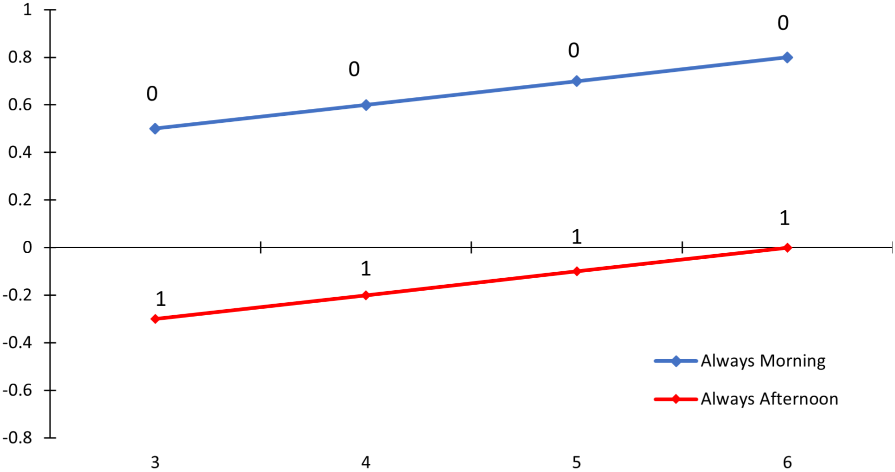
ϵ_{isbgt} is the error.

See details

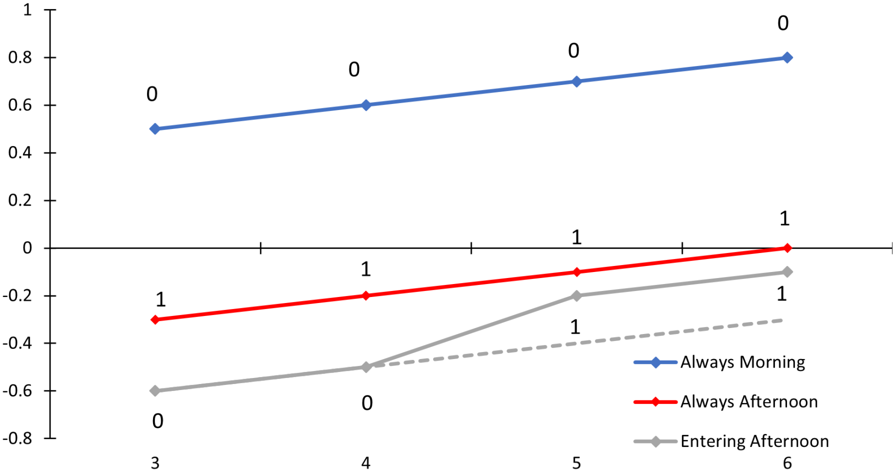
Case I: Always Morning



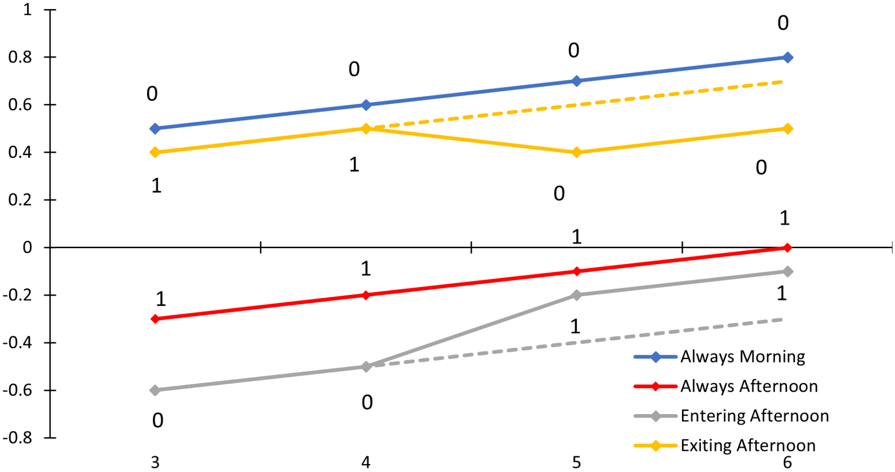
Case II: Always Afternoon



Case III: Entering Afternoon



Case IV: Exiting Afternoon



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.
  - Logit model See details
- Competition. If the opening of an afternoon school raises the level of morning schools.

Results

Table: Regression Results Verbal Test Scores

	(1)	(2)	(3)	(4)
Achievement Lag	0.0102	0.0102	0.0102	0.0101
	(0.0092)	(0.0092)	(0.0092)	(0.0092)
Afternoon	0.0570***	0.0567***		
	(0.0210)	(0.0210)		
Afternoon (Entering)			0.0756***	0.0942***
			(0.0280)	(0.0315)
Afternoon (Exiting)			0.0407	0.0219
			(0.0262)	(0.0304)
Non-struc Change		-0.0042		-0.0185
		(0.0110)		(0.0145)
Class Size	-0.0057***	-0.0057***	-0.0057***	-0.0057***
Observations	1,192,490			
Students	596,245			

Note: All regressions include individual and year fixed effects.

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

Results

Table: Regression Results Math Test Scores

	(1)	(2)	(3)	(4)
Achievement Lag	0.0571***	0.0571***	0.0571***	0.0571***
	(0.0113)	(0.0113)	(0.0113)	(0.0113)
Afternoon	0.0701***	0.0712***		
	(0.0222)	(0.0222)		
Afternoon (Entering)			0.1098***	0.1087***
			(0.0292)	(0.0331)
Afternoon (Exiting)			0.0352	0.0364
			(0.0275)	(0.0316)
Non-struc Change		0.0154		0.0012
		(0.0111)		(0.0149)
Class Size	-0.0052***	-0.0052***	-0.0052***	-0.0052***
	(0.0016)	(0.0016)	(0.0016)	(0.0016)
Observations	1,192,490			
Students	596,245			

Note: All regressions include individual and year fixed effects.

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

Results Quantiles

Table: Regression Results by Quartile

	(q1)	(q2 & q3)	(q4)
Verbal			
Entering	0.1469**	0.0679	0.0108
	(0.0598)	(0.0430)	(0.0551)
Exiting	0.0089	0.0077	0.0849
	(0.0563)	(0.0437)	(0.0539)
Math			
Entering	0.1646***	0.0712	0.0763
	(0.0604)	(0.0437)	(0.0590)
Exiting	0.0172	0.0475	0.0400
	(0.0577)	(0.0424)	(0.0576)

Conclusion

- This study quantifies school value added in afternoon schools relative to morning schools purging out unobserved student heterogeneity using panel data.
- The identification strategy relies on the movers.
  - No evidence that changes are driven by dips in achievement.
  - No evidence that there is an achievement cost in changing schools.
- The results show
  - Afternoon schools increase student achievement by 0.06 and 0.07 standard deviations in the verbal and math sections
  - The results are mainly driven by low achieving students entering the afternoon shift.

Next steps Duflo(2011), Hanushek(),...

Thank You!

Descriptive Statistics

Table: Morning and Afternoon School Differences

Panel A

year	**School Enrollment (# Students)**			**Class Size (# students)**			**Expenditure by Parents (Nominal Pesos)**		
	Morning	**Afternoon**	**Difference**	**Morning**	**Afternoon**	**Difference**	**Morning**	**Afternoon**	**Difference**
2008	425.9	262.5	163.4	32.7	25.6	7.1	1,043	894	148.3
2009	425.9	260.8	165.1	32.7	25.6	7.1	1,153	932	220.6
2010	424.7	260.3	164.4	32.7	25.7	7.0	1,245	990	254.8
2011	422.9	259.0	163.9	32.5	25.6	6.9	1,156	976	179.8
2012	418.7	254.3	164.4	32.0	25.1	6.9	1,184	989	195.2
2013	414.6	250.4	164.2	31.7	24.9	6.8	1,200	963	237.0

Panel B

year	**Women Ratio (%)**			**Repeaters (%)**			**Years in Teaching Carrer (per 100 students)**		
	Morning	**Afternoon**	**Difference**	**Morning**	**Afternoon**	**Difference**	**Morning**	**Afternoon**	**Difference**
2008	49.3	47.6	1.7	2.7	4.0	-1.3	1.8	2.4	-0.5
2009	49.4	47.6	1.8	2.4	3.8	-1.4	1.7	2.2	-0.5
2010	49.4	47.6	1.8	2.1	3.4	-1.3	1.6	2.0	-0.5
2011	49.4	47.7	1.7	2.0	3.2	-1.2	1.5	2.0	-0.5
2012	49.4	47.6	1.8	1.4	2.4	-1.0	1.5	2.0	-0.5
2013	49.4	47.6	1.8	0.5	1.0	-0.4	1.5	2.0	-0.5

Note: Based on matched schools. All differences are statistical significant at 1% level.

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 $\lambda = 1$

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Grade Change and Probability of School Switching

$$Pr(Switched_{isbgt} = 1) = logit^{-1}(\Delta A_{ibsg-1t-1} + \theta_i + \beta \mathbf{S})$$

where $Switched_{isbgt}$ takes the value of 1 if a student changed school at year t.

$\Delta A_{isbgt} = A_{isbgt} - A_{isbg-1t-1}$ is the difference in achievement.

θ_i are individual fixed effects.

S is a vector of school characteristics.

Logit Results

Table: Regression Results

	(1)	(2)	(3)
Δ Verbal TS	-0.0071		
	(0.0130)		
Δ Math TS		-0.0081	
		(0.0128)	
Δ Average TS			-0.0098
Observations	24,232		
Students	12,116		

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

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