Double-shift schooling and student success: Quasi-experimental evidence from Europe*

Lester Lusher[a], Vasil Yasenov[a]

[a]University of California, Davis

Abstract

School scheduling systems are frequently at the forefront of policy discussions around the world. This paper provides the first causal evidence of student performance during double-shift schooling systems. We exploit a six-year quasi-experiment from a country in Eastern Europe where students alternated between morning and afternoon school blocks every month. We estimate models with studentclass and month fixed effects using data on over 260,000 assignment-level grades. We find a small, precisely estimated drop in student performance during afternoon blocks.

Keywords: Gender Performance Gap; Gender Difference in Sleep Cycles; School Start Time

JEL codes: H52, I20, I21

*We would like to thank Mark Bray, Colin Cameron, Scott Carrell, Paco Martorell, Doug Miller, and Vladimir Tyazhelnikov for helpful comments. Nicholas Halliwell, Bhaverpreet Sidhu, and Catherine Jiang provided excellent research assistance.

1 Introduction

Over 45 countries spanning the five major continents currently implement double-shift schooling systems, where two populations of students get split into morning and afternoon blocks.[1] Students in the first session typically attend school from the early morning to the early afternoon, while the second session students arrive soon after the morning session ends and stay until the late afternoon. Because it enables a single set of resources (e.g. facilities, instructors, textbooks) to serve multiple cohorts of students, the main purpose of the double-shift system is to increase the supply of schools while minimizing costs. Policymakers often cite double-shift schooling systems as a way developing countries can attain universal primary and secondary education (Bray, 2008). While being most commonly implemented in developing countries (due to resource constraints) and urban areas (where population density is higher), double-shift schooling systems also exist in some prosperous societies, including the United States (Sagyndykova, 2013). While the cost-savings resulting from a double-shift schooling system are clear, policymakers shy away from introducing multiple shifts in schools. The principle debate centers on the lack of causal evidence of how student performance could be affected by taking classes during the afternoon block. Overall, detractors worry about potential drops in student performance during afternoon sessions. For example, students may choose to spend less time studying after school as afternoon hours become relatively scarce. The opportunity costs affiliated with attending school later in the day could also be higher for students. Furthermore, instructors who teach both morning and afternoon blocks may be more fatigued during their afternoon sessions. The prior literature has focused on using between school variation to document student performance in double-shift systems (e.g. Fuller et al., 1999; Herran and Rodriguez, 2000; Sagyndykova, 2013). By failing to utilize any

[1] These include Argentina, Bangladesh, Botswana, Brazil, Bulgaria, Burkina Faso, Cambodia, Chile, China, Democratic Republic of Congo, Dominican Republic, Egypt, Eritrea, Gambia, Ghana, Guinea, Hong Kong, India, Indonesia, 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.

exogenous variation in school block, these studies are entirely correlational in nature.[2] This paper provides the first causal evidence on student performance in double-shift schooling systems by exploiting a six-year quasi-experiment where cohorts of students alternated between morning and afternoon school blocks every month.

2 Data and institutional background

Our study focuses on a community of middle and high schoolers from 2008 to 2014. Each incoming middle and high schooler get assigned a cohort based on the students academic interests, and students only take classes with other students from their cohort for the remainder of their time in school. The data comprise of a complete list of raw, pen-to-paper grades received on all homework, quiz, and exam assignments. Each assignment received one of five integer grades, ranging from 2 (lowest) to 6 (highest). Raw grades were not curved or edited upon being graded.[3] Grades are normalized to a mean of zero and a standard deviation of one within a class,[4] where class is defined as a combination of a course (e.g. 10th grade Biology for science cohort) and school year (e.g. 20092010). Summary statistics are presented in Table 1.

Table 1: Summary statistics

	N	Mean	Std. Dev.
Assignment level			
Grade	262,197	4.360	1.359
Student level			
Male	1,111	0.443	0.497
Native ethnicity		0.778	0.415
Class level			
# of Students	1,212	23.389	3.443
STEM Field		0.399	0.490
Student by class level			
# of Assignments	28,103	9.330	5.379

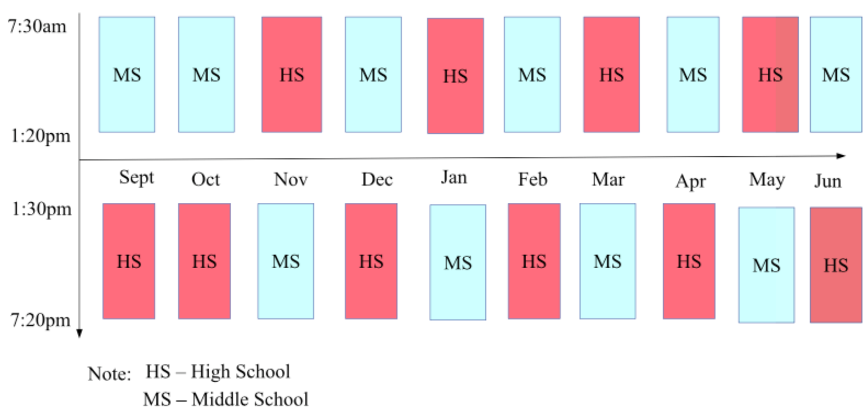
[2] A related strand of literature has focused on causally identifying the impacts of school start times on student outcomes (Carrell et al., 2011; Hinrichs, 2011; Edwards, 2012). Pope (2015) investigates the importance of school schedules on student performance.

[3] We do not analyze end-of-semester final grades, which may or may not have been curved.

[4] Meghir and Rivkin (2011) discuss how monotonic transformations of the outcome variable in a difference in difference setting could lead to changes in estimated signs and/or magnitudes. We consider several models using the raw, nonstandardized grades, and the results remain qualitatively similar.

During the period of our study, a variant of the double- shift schooling system was implemented where students, by cohort, alternated between morning and afternoon blocks each month. All other aspects of the schools were kept constant, including the ordering of classes within block and the teachers who taught the classes. High school cohorts were placed into morning blocks, which started at 7:30 AM and lasted until 1:20 PM, during September and the even months (October, December, February, April, and June), while middle school cohorts attended the morning block in all remaining odd months (November, January, March, and May). Thus, high (middle) school cohorts attended the afternoon block during odd (September and even) months. The afternoon block started shortly after the end of the morning block at 1:30 PM, and lasted until 7:20 PM (See Fig. 1). The quasi-experiment was implemented in response to local organizers inabilities to come to an agreement where cohorts remained entrenched in one block for the entire school year.

Figure 1: Quasi-experimental setting.



3 Identification Strategy

Our primary analysis estimates the following specification:

$$Grade_{aicmy} = \alpha + \beta \times LateBlock_{im}) + \boldsymbol{x}'_{aicmy}\gamma + \delta_{icy} + \lambda_m + \epsilon_{aicmy} \quad (1)$$

where $Grade_{aicmy}$ is the normalized grade student i received on assignment a in course c during month m and school year y. $LateBlock_{im}$ is an indicator variable equal to one if student is assignment was completed during an afternoon block month. X_{aicmy} is a vector of controls including the order of the assignment a and the number of assignments student i completed in class cy within month m. δ_{icy} are studentclass fixed effects, which control for mean differences in academic achievement for each studentclass combination. With δ_{icy}, not only do we control for unobserved class-level characteristics (e.g. teacher ability, class difficulty) and student-level characteristics (e.g. intelligence), but we also control for studentclass specific unobservables that may influence grades. Furthermore, since school block varies across students within month, we include month fixed effects m to control for any unobserved variables that vary by month and influence student performance (e.g. weather). Thus, our identification strategy effectively compares the performance of the same student in the same class across morning and afternoon school blocks. The coefficient can be interpreted as the average change in standardized grade in response to the afternoon block. Our estimates will be biased only if an omitted term correlates across every odd month, has power in predicting assignment grades, and differentially impacts high schoolers versus middle schoolers.

4 Results

Table 2 presents our main results. Each cell from Model 1 reports an estimated coefficient for $LateBlock_{im}$. Standard errors are two-way clustered at the student and class level (Cameron et al., 2011). Across all considered specifications, we attain statistical significance at the 1% level. From column (6), the full specification, we predict a 0.029 standard deviation decrease in assignment grade during the afternoon block.[5] Estimates are fairly insensitive across specifications. In Model 2, we interact $LateBlock_{im}$ with an indicator for whether the student was in high school. Similarly, in Model 3, we interact $LateBlock_{im}$ with

[5]For reference, Carrell et al. (2011) estimate a 0.140 standard deviation increase in student achievement in response to a one-hour delay in school start time. Pope (2015) finds a 0.021 standard deviation decrease in standardized math test scores for students who took math classes in periods 56 (12:502:45 PM) versus periods 12 (8:009:55 AM).

an indicator for classes that started between 7:30 to 8:30 AM in morning blocks and 1:30 to 2:30 PM in afternoon blocks. We report the coefficients and standard errors on the interaction terms on the bottom two rows of each model.

Table 2: Predicted effect of afternoon block on standardized assignment grade

	(1)	(2)	(3)	(4)	(5)	(6)
Model 1						
Late Block	-0.035^{***}	-0.034^{***}	-0.037^{***}	-0.036^{***}	-0.029^{**}	-0.029^{***}
	(0.012)	(0.012)	(0.009)	(0.009)	(0.014)	(0.010)
Model 2 — Age interactions						
Late Block	0.000	-0.007	0.003	-0.001		
	(0.077)	(0.076)	(0.047)	(0.048)		
X High Schoolers	-0.051	-0.039	-0.058	-0.051		
	(0.115)	(0.114)	(0.074)	(0.074)		
Model 3 — Period interactions						
Late Block	-0.033^{***}	-0.032^{***}	-0.035^{***}	-0.034^{***}	-0.027^{*}	-0.027^{***}
	(0.012)	(0.012)	(0.009)	(0.009)	(0.014)	(0.010)
X Period 1–2	-0.022	-0.022	-0.023	-0.023	-0.023	-0.024
	(0.058)	(0.058)	(0.029)	(0.029)	(0.058)	(0.028)
Observations	261053	261053	261053	261053	261053	261053
Controls		X		X	X	X
Class FE	X	X			X	
Student FE	X	X			X	
Student X Class FE			X	X		X
Month FE					X	X

Notes: Each column and model consider a separate regression. Standard errors in parentheses are two-way clustered by student and by class. Controls include the order of the assignment and the number of assignments the student completed in the class within the month.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

Notes: Each column and model consider a separate regression. Standard errors in parentheses are two-way clustered by student and by class. Controls include the order of the assignment and the number of assignments the student completed in the class within the month. * p ¡ 0.10.; ** p ¡ 0.05.; *** p ¡ 0.01.

We find little evidence of differential responses by student age or by ordering of the class. We also fit ordered probit and (fixed effect) ordered logit models on the raw grades data in Table 3. Panel A displays the coefficient of $LateBlock_{im}$, while Panel B presents marginal effects of the afternoon school block on the probability of obtaining each grade evaluated at the controls means. The final column presents results from the ordered logit model with studentclass fixed effects using the Das and Van Soest (1999) estimator.[6] The probability of obtaining a low grade (2, 3 or 4) slightly increases in response to the afternoon shift.

[6]Cameron and Trivedi(2005) describe the basic setup of ordered logit and probit models, while Baetschmann et al. (2014) discuss the arising problems in estimation of fixed effects ordered logit models and summarize the proposed solutions. The fixed effect ordered logit estimator does not permit computation of marginal effects, but the larger coefficient in Panel A indicates an increase in the effect on the latent variable.

Table 3: Predicted effect of $LateBlock_{im}$ on raw assignment grade

	Ordered Probit	Ordered Logit	Fixed effects Ordered Logit
Panel A:			
Late Start	-0.028^{***}	-0.048^{***}	-0.087^{***}
	(0.004)	(0.007)	(0.008)
Panel B:			
Marginal Effects:			
$Pr(y=2)$	0.006^{***}	0.005^{***}	–
	(0.001)	(0.001)	
$Pr(y=3)$	0.004^{***}	0.005^{***}	–
	(0.001)	(0.001)	
$Pr(y=4)$	0.002^{***}	0.002^{***}	–
	(0.000)	(0.000)	
$Pr(y=5)$	-0.002^{***}	-0.003^{***}	–
	(0.000)	(0.000)	
$Pr(y=6)$	-0.009^{***}	-0.009^{***}	–
	(0.001)	(0.001)	
Controls	X	X	X
log L	−401,121	−400,951	–
$R^2 \backslash$ Pseudo R^2	0.024	0.024	–
N	261,053	261,053	253,280

Notes: Panel B presents marginal effects of the afternoon school block on the probability of obtaining each grade at the controls' means. The final column includes student–class fixed effects.

* $p < 0.10$
** $p < 0.05$.
*** $p < 0.01$.

Notes: Panel B presents marginal effects of the afternoon school block on the probability of obtaining each grade at the controls means. The final column includes studentclass fixed effects. * p¡0.10; ** p ¡ 0.05; *** p ¡ 0.01.

4.1 Conclusions

Policymakers around the world regularly deliberate over optimal school scheduling systems. This paper utilizes within studentclass and within month variation in school block to find a small, precisely estimated drop in student performance during afternoon blocks. Overall, the evidence suggests that the double- shift system may be a cost-effective policy communities can implement to combat resource constraints.

References

[1] Baetschmann, G., Staub, K.E., Winkelmann, R., 2014. Consistent estimation of the fixed effects ordered logit model. J. Roy. Statist. Soc. Ser. A.

[2] Bray, M., 2008. Double-shift Schooling: Design and Operation for Cost- Effectiveness. Commonwealth Secretariat.

[3] Cameron, A.C., Gelbach, J.B., Miller, D.L., 2011. Robust inference with multiway clustering. J. Bus. Econom. Statist. 29.

[4] Cameron, A.C., Trivedi, P.K., 2005. Microeconometrics: Methods and Applications. Cambridge University Press.

[5] Carrell, S.E., Maghakian, T., West, J.E., 2011. As from Zzzzs? The causal effect of school start time on the academic achievement of adolescents. Am. Econ. J. Econ. Policy 3, 6281.

[6] Das, M., Van Soest, A., 1999. A panel data model for subjective information on household income growth. J. Econ. Behav. Organ. 40, 409426.

[7] Edwards, F., 2012. Early to rise? The effect of daily start times on academic performance. Econ. Educ. Rev. 31, 970983.

[8] Fuller, B., Dellagnelo, L., Strath, A., Bastos, E.S.B., Maia, M.H., de Matos, K.S.L., Portela, A.L., Vieira, S.L., 1999. How to raise childrens early literacy? The influence of family, teacher, and classroom in northeast Brazil. Comp. Educ. Rev. 135.

[9] Herran, C.A., Rodriguez, A., 2000. Secondary Education in Brazil: Time to move forward, Tech. Rep.. Inter-American Development Bank.

[10] Hinrichs, P., 2011. When the bell tolls: The effects of school starting times on academic achievement. Education 6, 486507.

[11] Meghir, C., Rivkin, S., 2011. Econometric methods for research in education. Handb. Econ. Educ. 3, 187.

[12] Pope, N.G., 2015. How the time of day affects productivity: evidence from school schedules. Rev. Econ. Stat.

[13] Sagyndykova, G., 2013. Academic Performance in Double-shift Schooling. University of Arizona, Tucson, p. 85721.