AFEP | Africa Fellows in Education Program

GLOBAL EDUCATION ANALYTICS INSTITUTE
Putting evidence at the heart of education policy

AFEP WORKING PAPER

Double-Shift Schooling System and Learning Outcomes: A Nonparametric Bounds Analysis

Amadou Jallow
University of The Gambia

May 2025

Acknowledgements

This work was carried out with financial and scientific support from the Partnership for Economic Policy (PEP) and the Global Education Analytics Institute (GEAI) through funding provided by the Yidan Foundation. The author thanks Ramaele Moshoeshoe, Director of AFEP, and fellow AFEP fellows Heleen Hofmeyr, Jaah Mkupete and Yselle Flora Malah Kuete for valuable comments on earlier drafts. He also thanks participants at the World Bank Africa Fellowship Seminar, the 2024 PEP Annual Workshop and the CSAE pre-conference workshop at the University of Pretoria, colleagues at the University of The Gambia, and Daniel Rodriguez, Moussa Blimpo, Kathleen Beegle, S. Anukriti and other colleagues at the World Bank for helpful feedback.

Any opinions, findings and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the Partnership for Economic Policy (PEP) or the Global Education Analytics Institute (GEAI).

Double-Shift Schooling System and Learning Outcomes: A Nonparametric Bounds Analysis

Amadou Jallow*

University of The Gambia

May 2025

Abstract

The double-shift schooling system, which groups students into morning and afternoon shifts, has been implemented in many developing countries as a cost-effective strategy to increase access to education. However, empirical evidence of its impact on learning outcomes is limited. This study aims to inform the ongoing policy debate about the trade-offs between increasing access and maintaining quality by examining how the double-shift system (DSS) affects learning outcomes in The Gambia. It applies Manski's non-parametric bounds approach, relies on relatively weak and partially testable assumptions to further tighten the bounds, and uses students' household socio-economic status as an instrumental variable. The study finds that the DSS has a marginally negative effect on foundational literacy and high school performance.

Keywords: Double-Shift System, Non-Parametric Bounds

* University of The Gambia. Fellow, Africa Fellows in Education Program (AFEP), Cohort 1 (2023–2025).

1 Introduction

Access to education has increased significantly in many developing countries in the past few decades, yet learning outcomes remain poor. For instance, in Latin America despite a gross enrollment rate of 106%, it is estimated that four out of five children lack basic reading comprehension skills (World Development Indicators, 2022; The State of Global Learning Poverty, 2022). In Sub-Saharan Africa, the situation is worse, with an estimated 86.7% of children classified as "learning poor"[1] (Azevedo et al., 2021).

In many countries, the issue of poor learning outcomes has been partly associated with the implementation of the double-shift system (DSS)[2] to increase access (Linden, 2001). This system enables governments to expand access to education by scheduling two student groups—one in the morning and one in the afternoon—for shorter sessions, which maximizes existing facilities without requiring additional infrastructure, materials, or teachers (Bray, 2008; Kebbie, 2022). However, by design, this generally results in fewer instructional hours, which potentially affects learning outcomes. For instance, in The Gambia, the single-shift system (SSS) provides about 32 hours of weekly contact (inclusive of after-school classes) and the DSS provides about 24 hours of weekly contact on average. In the absence of the DSS, schools follow the traditional SSS, also known as a whole-day schedule, which serves one group of students for the entire day with regular morning classes and after-school remedial sessions. While the DSS has increased enrollment, concerns about learning outcomes have prompted debates over its effectiveness and calls in some countries[3] to abolish it (Ovalle-Ramirez, 2018).

A key question is whether transitioning from the DSS to the SSS would improve learning outcomes under the prevailing conditions and, if so, to what extent. Despite its significance, this question has received little attention in the empirical literature[4]. Existing studies largely consist of descriptive case analyses (Bray, 2008; Singadi et al., 2014; Bervell et al., 2013) or focus on the morning vs. afternoon shifts in double-shift schools, and have yielded mixed results (Lusher and Yasenov, 2016; Pedroza, 2018). The scarcity of empirical studies on the DSS's effect stems largely from identification challenges, including selection bias and the lack of exogenous variation in the adoption and implementation of the DSS in most developing countries. The decision to opt for the DSS or the SSS and students' choices between the two are typically non-random and influenced by unobserved factors.

[1] "Learning poverty" refers to being unable to read and understand a simple text by age 10 (World Bank, 2019).

[2] This system has been adopted in more than 45 developing countries (Lusher and Yasenov, 2016).

[3] Countries include Jamaica, Columbia, and Ghana, among others.

[4] See Bray (2008) for a detailed discussion on the design and operationalization of the DSS.

This study attempts to fill this gap in the literature by empirically examining the causal effect attending a double-shift school has on learning outcomes[5] at both the foundational level (i.e., in Grades 1, 2, and 3) and the high school level (i.e., in Grade 12) using The Gambia as a case study. It relies on data from the Gambian Ministry of Basic and Secondary Education (MoBSE) on Early Grade Reading Assessment (EGRA) results for 2016 and West African Senior School Certificate Examination (WASSCE) results for 2015–2019. Notably, both datasets are devoid of exogenous variation in schools' implementation of the DSS or in student allocation across shift systems (DSS and SSS), which limits the potential to make use of this type of variation for identification purposes when estimating causal effects.

To circumvent the identification challenges, this study employs the partial identification approach proposed by Manski and Pepper (2000) to "set identify" causal effects by deriving upper and lower bounds on the treatment effects. This method is particularly useful for addressing selection bias in the presence of unobserved variables that may influence both treatment assignment and outcomes (Manski and Pepper, 2000; De Haan, 2011; Cygan-Rehm et al., 2017; Germinario et al., 2022). Manski and Pepper's approach offers two key advantages over traditional methods: (1) it relies on relatively weak and partially testable assumptions, and (2) it derives bounds on the average treatment effect (ATE) without imposing strong assumptions, such as regarding specific functional forms, the distributions of unobservables, or the homogeneity of the DSS's effect (see Manski and Pepper, 2000). Given the nature of the data, the dearth of studies investigating the effect the DSS has on learning outcomes, and the lack of compelling empirical evidence in the literature, a non-parametric bounding technique is a valuable and credible method for understanding the extent of the DSS's effect.

This study's analysis starts with an exploration of the insights that the data can offer about the impact school shift systems (SSS vs. DSS) have on academic performance without any assumptions being imposed. Weak non-parametric assumptions are then added to tighten the bounds and enhance the precision of the effect estimates. The analysis relies on three key assumptions: (1) monotone treatment selection (MTS), which assumes that students in double-shift schools are negatively selected and generally have lower test score potential than those in single-shift schools; (2) monotone treatment response (MTR), which asserts that attending a double-shift school does not lead to higher test scores than attending a single-shift school; and (3) a monotone instrumental variable (MIV), which is assumed to have a weakly monotonic mean relationship with potential test scores. Students' household socio-economic status (SES) is used as the MIV,

[5] There also exist other dimensions through which the DSS could be assessed. For instance, Dominguez and Ruffini (2023) investigate the long-term benefits of longer school days, which include delayed childbearing and increased earnings.

and the assumption is that higher SES values correlate with higher average test scores[6]. The descriptive analysis of EGRA data presents evidence that supports these assumptions.

The study analyzes public primary schools (EGRA data) and private high schools (WASSCE data). It finds that attending a double-shift school negatively affects student learning outcomes at both the foundational and high school levels; however, the effects are often marginal and sometimes statistically insignificant. For example, in the worst-case scenario, attending a public double-shift school reduces standardized oral reading fluency (ORF) scores by 0.43 standard deviations. Incorporating the MTS, MTR, and MIV assumptions reduces the bounds to between -0.018 and -0.007 standard deviations. These bounds are tighter and narrower than the -0.12-standard deviation estimate assuming exogenous treatment selection (ETS), which likely overstates the negative effect.

At the high school level, attending a private double-shift school substantially reduces the likelihood of passing both English and Mathematics, with worst-case bounds indicating up to a 79% decrease. Applying the MTS and MTR assumptions reduces this effect to approximately 7.2 percentage points. The results are similar for the probability of obtaining five credits including English and Mathematics.

Analyses of EGRA data subsamples show that Grade 1 students are more adversely affected by the DSS than Grade 2 and 3 students across all subtasks. Gender disaggregation reveals that the negative impact is nearly three times greater for girls than for boys, and regionally, the DSS's effect is negative in Region 1 but positive in Region 2. Similar heterogeneity is observed in the WASSCE data, with the DSS exerting a stronger negative effect on performance in Mathematics than in English.

This study's marginal effect estimates are smaller than the 0.1-standard deviation improvement Smart (2023) reports Jamaica observed after it phased out the DSS. Related studies on DSS shift timing have found even smaller effects. For instance, Lusher and Yasenov (2016) report a 0.029-standard deviation decrease in assignment grades for afternoon-shift students versus morning-shift students[7]. Research on instructional time—an important factor that differentiates the DSS from the SSS—also aligns with these findings. Studies by Barrios-Fernández and Bovini (2021) and Cabrera-Hernández (2020) show that extending the school day improves Mathematics and language performance on low-stakes exams, with effects ranging from 0.015 to 0.14 standard deviations—comparable to those found here. However, these reforms often include complementary interventions, such as teacher training, that make it more difficult to isolate the effect of increased instructional time.

[6] The assumption is that larger class sizes or higher PTR are associated with lower average test scores due to factors like less individual attention from teachers or increased classroom management challenges. Similar assumptions are made about students from disadvantaged socio-economic backgrounds.

[7] And Arceo-Gómez et al. (2018) report that attending afternoon shifts increases the high school dropout risk by about 12 percentage points in Mexico, though they do not directly measure learning outcomes.

This study advances the literature on the DSS in several important ways. First, it provides rigorous empirical evidence from a resource-constrained developing country where the DSS is not only widespread—encompassing nearly 50% of primary and almost 90% of high school enrollment—but also coincides with some of the lowest learning outcomes in the subregion. In this context, debates around abolishing the DSS are driven primarily by concerns over educational quality rather than cost or access, and this nuance is often overlooked in the global discourse.

Second, this is the first study to systematically evaluate how the DSS impacts both foundational and upper secondary learning outcomes and distinguish between public and private schools in the same national context. By disaggregating effects by educational level and school type, the analysis provides critical insights into where and for whom the DSS's negative effects are most pronounced and thereby informs more targeted policy interventions.

Third, unlike most prior research that focuses exclusively on either low-stakes or high-stakes assessments, this study examines student performance on both types of assessments by considering standardized literacy tests (the EGRA) at the foundational level and a high-stakes exit exam (the WASSCE) at the secondary level. This dual focus provides a more comprehensive understanding of the breadth and depth of the DSS's impact on educational achievement.

Finally, this study makes a novel methodological contribution to the literature by employing a non-parametric bounds technique to address the identification challenges that are inherent in estimating the DSS's causal effects. This approach makes it possible to estimate informative bounds on policy-relevant parameters without relying on strong, often untenable, linearity or homogeneity assumptions. This methodological innovation is particularly valuable in data-limited settings where policy decisions must be made in the face of uncertainty, which are common in developing countries.

Together, these contributions not only fill critical empirical and methodological gaps in the literature on the double-shift schooling system but also provide actionable evidence for policymakers navigating the trade-offs between expanding access and improving quality in education systems under severe resource constraints.

The remainder of this paper is structured as follows. Detailed background and contextual information are provided Section 2. Section 3 describes the two sets of assessment data analyzed, and Section 4 explains the empirical framework used. Section 5 presents the main results, additional estimate / robustness check results, and the heterogeneity analysis. Lastly, Section 6 concludes the paper.

1.1 Background and Context

The Gambian school system is structured such that most students begin Lower Basic School (Grade 1) at age 7, with only a few attending pre-primary education (Early Childhood Develop-

ment centers or Nursery School) starting at age 3 or 4 before transitioning to Lower Basic School at age 6 or 7. Students typically spend six years in Lower Basic School (Grades 1–6), followed by three years in Upper Basic School (Grades 7–9) and three years in High School (Grades 10–12).

As in many resource-constrained developing countries, the DSS is widely used in The Gambia, particularly in public schools (Lusher and Yasenov, 2016). In 2023, over 70% of public schools (primary and secondary) followed a DSS model, compared to only 13% of private schools (MoBSE Education Statistics, 2023). Several forms of DSS exist, including weekly or bi-weekly rotations between morning and afternoon shifts, permanent morning or afternoon shifts, double-shifting of schools only, and double-shifting of both schools and teachers. Most double-shift schools follow an "end-on" model, where one group of students ends their classes before the next group starts (Bray, 2008).

Schools typically start the day at 8:00 a.m., with lessons beginning at 8:30 a.m. In single-shift schools, classes run from 8:30 a.m. to 1:30 p.m.—and are followed by study sessions from 2:00 p.m. to 4:00 p.m.—Monday to Thursday and end at 12:30 p.m. on Fridays. In double-shift schools, the morning shift runs 8:30 a.m. to 1:30 p.m. (12:30 p.m. on Fridays), after which morning-shift students leave. The afternoon shift starts around 1:45 p.m. (12:45 p.m. on Fridays) and ends by 6:00 p.m. Morning-shift students in double-shift schools receive comparable instructional hours to students in single-shift schools. However, afternoon-shift students receive approximately 30–45 minutes (10–15%) fewer instructional hours per day from Monday to Thursday than their morning-shift counterparts. This reduction is partially compensated by an additional 1–1.5 hours of instructional time on Fridays.

Schools' decision to implement the DSS largely reflects student demand for a school, which is influenced by factors such as the school's past exam performance. At the primary level, enrollment in single-shift or double-shift schools depends mainly on student or parental choice, which is constrained by accessibility, affordability, and school capacity. Since most single-shift schools are urban, rural students have limited access to them, which makes attendance largely endogenous but unrelated to prior academic achievement. In contrast, admission to single-shift or double-shift high schools depends on students' performance on the Grade 9 Gambia Basic Education Certificate Examination, high school preferences, location of residence, and household SES. Placement in a specific school and shift is influenced by school-specific cut-off marks that are tied to capacity and may differ from national standards.

As in other English-speaking West African countries like Nigeria, Ghana, Sierra Leone, and Liberia, in The Gambia, students sit for the WASSCE at the end of Grade 12. Gambian students' performance on this high-stakes exam is a crucial factor in their ability to access higher education and future labor market opportunities. Unlike the Grade 9 exam, which is country-specific, the WASSCE is a standardized regional exam. Grade 12 students can take up to nine subjects, including core courses such as English, Mathematics, and Science. Grades range from A1 (Ex-

cellent) to F9 (Fail), with intermediate grades like B2 (Very Good), B3 (Good), and C4–C6 (Credit). Students scoring D7 or E8 pass but fall below credit level. In The Gambia, obtaining credits in at least five subjects including English and Mathematics qualifies students for direct university admission. This differs from countries like Nigeria, where additional university entry exams are required. However, only about 5% of Gambian students meet the benchmark, compared to 30–50% of students in Sierra Leone and Ghana, and over 70% of students in Nigeria.

1.2 Conceptual Framework

Less instructional time, fewer opportunities for extra classes, limited curriculum coverage, and student and teacher fatigue—especially among afternoon-shift students—have all been identified as potential channels through which the DSS may affect learning outcomes (Linden, 2001a; Bray, 2008; Singadi et al., 2014; Bervell et al., 2013). However, there is limited evidence supporting these claims. For instance, Bray (2000) studied five countries, including Malaysia, the Philippines, and Zambia, and found there were significant differences in official hours between school shift systems only in the Philippines, with variations ranging from 7% in lower secondary to 10% in upper secondary. Similarly, Smart (2023) reported that phasing out the DSS increased instructional time in Jamaica by 2.5 hours per week (about 10%). Therefore, it is crucial to pin down the factors that are most relevant in the case of The Gambia to be able to speak to the mechanism(s) at play.

The most obvious channel through which the DSS may impact learning outcomes is fewer instructional hours and less time spent in school. As Bray (2008), Singadi et al. (2014), and Bervell et al. (2013) have highlighted, the DSS inherently allows for less instructional time than the SSS. In The Gambia, the average weekly instructional time is about 33% less in double-shift schools than in single-shift schools largely because the DSS crowds out after-school study classes. It is worth mentioning that in the absence of after-school classes, the difference in regular instructional hours is very minimal (less than 10%). While a 10% reduction in regular instructional hours may impact learning outcomes, it is unlikely to be the main factor behind them. For instance, Smart (2023) showed that a 10% increase in instructional time in Jamaica from phasing out the DSS increased average test scores by only 0.1 standard deviations. A more significant factor is the DSS's crowding out of extra classes, which leads to a combined difference of 33–40% fewer instructional hours per week in double-shift schools. If single-shift schools make effective use of their additional hours, this could lead to significant differences in the learning outcomes of single-shift and double-shift students.

A second channel is the effect of teacher "double-shifting". In many developing countries including The Gambia, teachers in double-shift schools often teach in both the morning and afternoon shifts, either at the same or different schools, to supplement their low income (Nhundu,

2001). This can lead to exhaustion and reduced productivity, which disadvantages students in double-shift schools, especially those in the afternoon shift (Singadi et al., 2014). However, this issue is not exclusive to double-shift schools; teachers in single-shift schools may provide private tutoring or extra classes outside of their regular 2–4 p.m. study classes at school. While the impact teacher double-shifting has on performance differences between single-shift and double-shift students cannot be dismissed outright, it is not expected to be a determining factor, especially in performance differences between single-shift students and morning-shift students in double-shift schools.

A third channel that has been identified in the literature is the role of weather conditions. In The Gambia, temperatures are significantly hotter in the afternoon than at other times of the day, particularly in the hinterlands, and hotter temperatures are less conducive to learning (see Park et al., 2021; Alberto et al., 2021). Consequently, afternoon-shift students in double-shift schools may be further disadvantaged by temperatures negatively impacting their learning outcomes and contributing to disparities in student performance between the DSS and the SSS. However, this issue is not exclusive to double-shift schools; it may also affect single-shift students attending after-school study classes (the main source of differences in instructional hours) that are scheduled in the afternoon.

Bray (2008) highlighted that the reduction in instructional hours, and therefore time spent in school, may lead to idleness, child labor and unproductive lifestyles among students (Linden, 2001b). There exists evidence indicating that girls are negatively affected by the DSS through an increase in household chores and farm labor, especially in rural areas (Kea, 2007). Spending less time at school translates to an increase in household responsibilities for girls. This is especially the case for girls who attend the afternoon shift at double-shift schools. As is the case for boys, they are more likely to engage in farm labor and play when they spend less time in school (Kea, 2007). Therefore, it cannot be ruled out that student fatigue arising from increased household chores and play may contribute to lower learning levels and negatively impact the overall performance of students in double-shift schools, especially afternoon-shift students.

However, the possibility that teachers and students in double-shift schools may adopt strategies to offset challenges associated with the DSS cannot be discounted. Teachers may specialize by subject and grade to improve their proficiency and assign extra homework to supplement limited instruction time. Students may put in more effort and form study groups to reinforce learning. While such strategies may also occur in single-shift schools, the fact that there are fewer classes per grade and longer school days potentially limits their scale in single-shift schools compared to double-shift schools.

Based on the above discussion, the most significant factor in The Gambia appears to be the substantial reduction (33–40%) in total weekly instructional hours under the DSS, which is largely due to the loss of after-school study classes rather than modest differences in regular class

time. While teacher double-shifting, adverse afternoon conditions, and increased household responsibilities and fatigue are also potential channels, they are unlikely to be the main channels through which the DSS impacts learning outcomes, if at all.

1.3 Data

This study relies on two sets of assessment data from the Gambian MoBSE: EGRA results for 2016 and WASSCE results for the period 2014–2019. The 2016 EGRA was administered to 3,000 students in Grades 1–3 who were randomly selected from 181 schools and is nationally representative. However, missing data and challenges merging the teacher and student records resulted in the initial analytic sample being reduced to 2,706 successfully merged student records. Further restricting the sample to public schools in order to minimize contamination when comparing the DSS and the SSS yielded a final sample of 2,180 students. In contrast, the WASSCE is an international exam that is taken by Grade 12 students across the country. However, since approximately 98% of public high school students attend double-shift schools, the analysis is restricted to private high schools, where about 56% of students are enrolled in double-shift schools. Together, these datasets make it possible to investigate how the DSS impacts the early and later stages of students' educational journey.

The EGRA data serve to understand the effect the DSS has on foundational learning, as the EGRA primarily assesses foundational literacy skills. The main variable of interest in the EGRA data is the ORF subtask, which evaluates students' ability to read sentences fluently. Other outcome variables include the letter sound identification subtask, which assesses students' ability to correctly pronounce the phonetic sounds of individual letters, and the familiar word identification subtask, which measures students' ability to distinguish familiar words that sound different from a group of words. Together, these skills form the foundation for word formation, word identification, and the development of reading comprehension. The dataset includes not only individual subtask scores but also information about student demographics, students' household SES, and school and teacher attributes. Importantly for this study, the dataset also contains information on the school's shift type (double-shift or single-shift), the shift the student attends (morning or afternoon, if a double-shift school), and the school type (government, grant-aided, or private).

The WASSCE data are used to investigate how the DSS affects student performance in high school. WASSCE performance is a major determinant of access to post-secondary education and the primary criterion for university admission in The Gambia. The WASSCE dataset contains each student's score for each subject covered in the exam, their gender, the location (region) of their school, and their school's shift type (double-shift or single-shift) and school type (government, grant-aided, or private). The primary outcome variable analyzed in this study is the probability of passing both English and Mathematics. Additional outcome variables include the

proportion of students obtaining credits in at least five subjects including English and Mathematics, as well as the disaggregated effects on the probability of passing English and Mathematics separately. Unlike the EGRA dataset, the WASSCE dataset does not contain information on student demographics or school and teacher characteristics. Therefore, the descriptive statistics regarding the assumptions rely solely on EGRA data. The EGRA dataset overcomes two key limitations of the WASSCE dataset: limited variability in public double-shift and single-shift school attendance, and insufficient data to test the assumptions.

1.4 Summary Statistics

Between 2014 and 2019, around 82% of all high schools with registered students followed the DSS, and their enrollment accounted for about 90% of all Gambian students who took the WASSCE. Notably, there is considerable regional variation in both the prevalence of the DSS and the share of the population attending double-shift schools. The high prevalence of the DSS in The Gambia provides suggestive evidence that the DSS has been the primary means through which the government has been able to increase access to education.

In terms of performance, students obtain an average of 2 credits (grades A1–C6) and about 3.5 passes (grades D7 or E8) across all subjects. The overall average score per student is a passing grade of 7.7. Performance is notably better in English (mean = 7.7) than Mathematics (mean = 8.3). Approximately 19% of students passed both English and Mathematics as well as their other subjects. About 49% of students obtained a passing grade in English, and about 26% did so in Mathematics. On average, over the period 2014–2019, only about 6% of students in private high schools obtained credits in five subjects including English and Mathematics. Table A1 in the appendix provides summary statistics for the WASSCE data used.

Approximately 32% of the students in the full EGRA sample were enrolled in double-shift schools, compared to about 40% of the students in the sample restricted to public schools. About 80% of students attended public schools (government or grant-aided). The average number of students per grade and school was about 87 for the full sample and 99 for the restricted sample, with significant variation, ranging from 4 students in the smallest school to 659 in the largest. As can be seen in Table A2 in the appendix, the number of classes per grade reached as high as 11 in some schools, though the average was 2.7. Dividing the number of students per grade by the number of classes per grade yielded the average class size, which is also referred to as the pupil–teacher ratio (PTR)[8]. The PTR was approximately 35:1 for the full sample and 37:1 for the restricted sample, with a range of 4–195. As for learning outcomes, students' scores on the

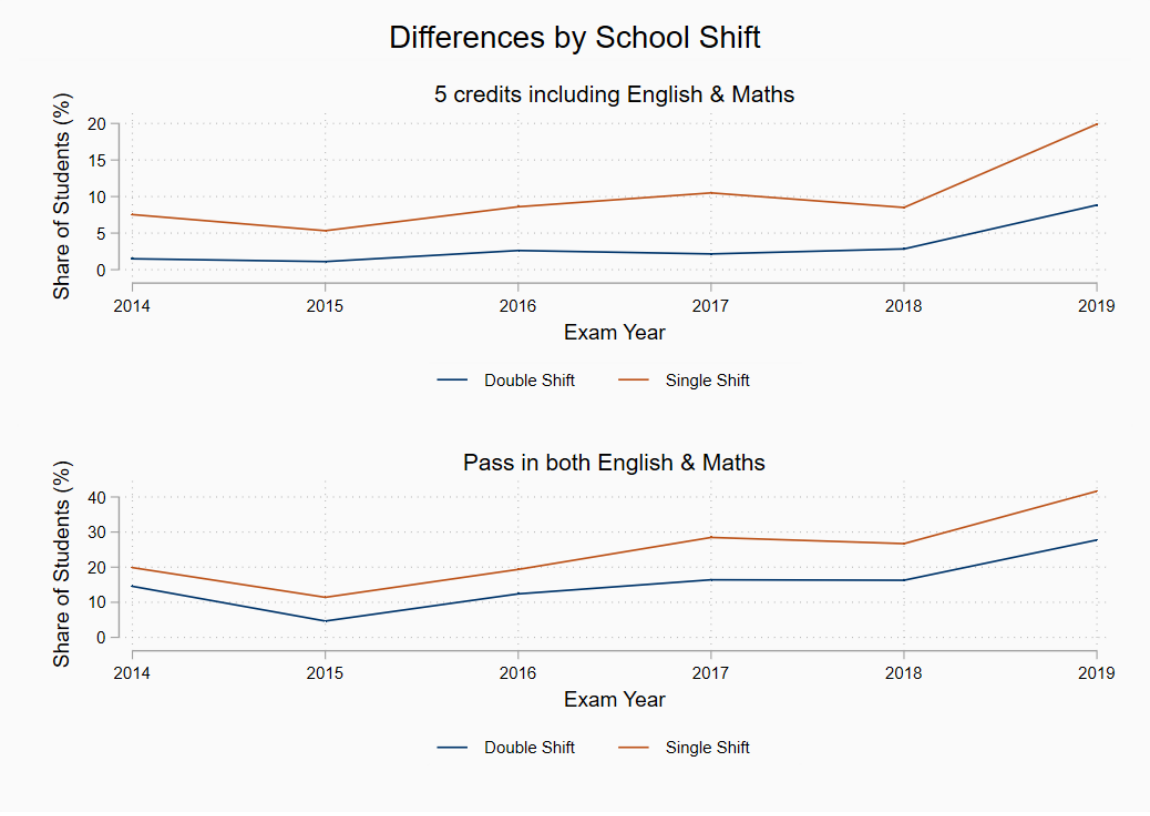
[8] It should be noted that while the number of classes in each grade would be expected in theory to be a perfect proxy for the number of teachers, this is not necessarily the case in double-shift schools. Teachers in double-shift schools may teach up to two classes of the same grade.

EGRA subtasks were standardized. On average, students obtained a score of 0.13 on the ORF subtask, 0.17 on the letter sound subtask and 0.14 on familiar word subtask.

1.5 Descriptive Analysis

When the data is disaggregated by school shift system (DSS vs. SSS), it is evident that students attending double-shift schools exhibit poorer learning outcomes than those in single-shift schools. For instance, the WASSCE results indicate approximately 24% of single-shift students and 15% of double-shift students passed both English and Mathematics. Similarly, only about 3% of double-shift students obtained credits in five subjects including English and Mathematics, compared to 10% of single-shift students on average. See the figure below for a graphical illustration.

Figure 1: Share of students by school shift system with (a) 5 credits including English and Mathematics, and
(b) a pass in both English and Mathematics

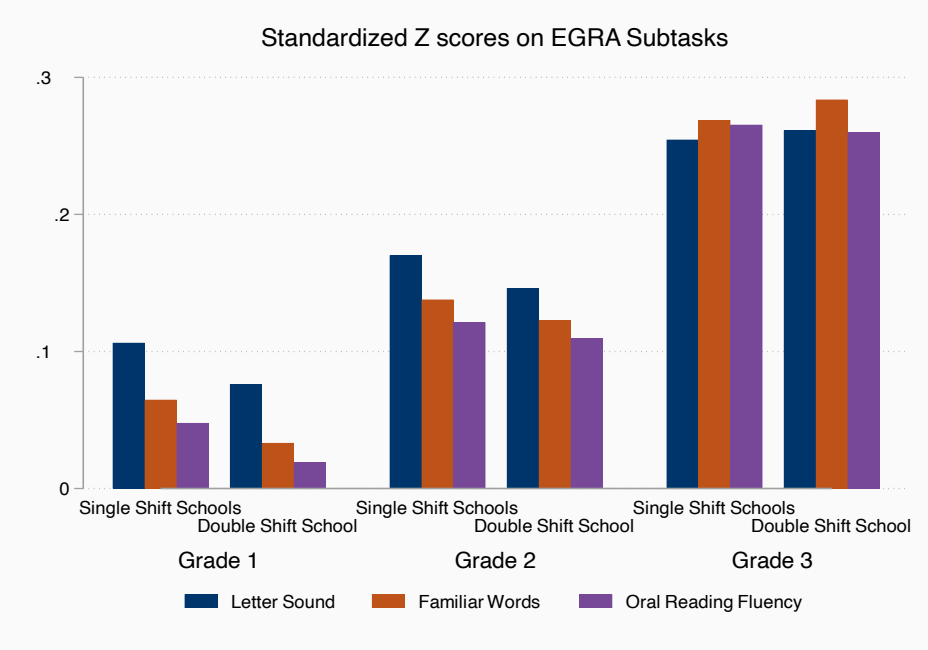


Notes: Source: Author's calculations based on available data. The top graph indicates the share of students that obtained five credits including English and Mathematics, and the bottom graph indicates the share of students that obtained a pass in both English and Mathematics. Both graphs report by school shift system over the period 2014–2019. The y-axis indicates the percentage of students, and the x-axis indicates the year in question.

At the foundational level, differences between single-shift and double-shift students' performance on EGRA subtasks are minimal and mostly statistically insignificant. When the data is

disaggregated by grade, Grade 1 single-shift students outperform their double-shift peers, but the gap narrows in Grade 2 and disappears in Grade 3.

Figure 2: Difference in standardized scores between single-shift and double-shift schools



Notes: Source: Author's calculations based on 2016 EGRA data.

The descriptive evidence presented above supports the general belief that students attending double-shift schools have relatively poorer learning outcomes than those attending single-shift schools.

2 Empirical Strategy

The empirical methodology used relies on the non-parametric bounds approach developed by Manski (1997) and Manski and Pepper (2000), which identifies upper and lower bounds on mean potential outcomes when outcomes are bounded. This approach estimates causal effects under minimal assumptions and accommodates the DSS having non-linear effects.

For each student i, the response function $Y_i(t)$ maps treatment $t \ \varepsilon \ \{0, 1\}$ (where $t = 1$ indicates the DSS and $t = 0$, the SSS) to exam scores $Y_i(t)$. Each student's actual treatment t and outcome $Y_i = Y_i(t)$ are observed, but not the counterfactual outcome$Y_i = Y_i\left(t'\right)$ for $t' \neq t$ is not. The goal is to estimate the ATE of the DSS versus the SSS as follows:

$$(1, 0) = E\left[Y(1)\right] - E\left[Y(0)\right] \tag{1}$$

where$E\left[Y(1)\right]$and$E[Y(0)]$ are the mean outcomes if all students attended double-shift or single-shift schools, respectively. Using the law of iterated expectations, $E[Y(1)]$ can be expressed as a weighted average of observed outcomes conditional on treatment status:

$$E[Y(1)] \;=\; E[Y|t=1]*P(t=1) + \; E[Y|t=0]*P(t=0)$$

However, only one of the conditional means—$E[Y|t=1]$ or $E\left[Y|t=0\right]$—is observed for each student, which creates a selection problem since treatment assignment depends on unobserved factors. To identify the causal effect, the observed data are supplemented with plausible assumptions about the unobserved counterfactual outcomes so that the ATE can be bounded without relying on strong parametric assumptions.

2.1 Manski's No-Assumption or Worst-Case Bounds

Manski (1997) showed that the bounds of the dependent variable can be identified without any additional assumptions if the outcome variable is bounded. In this study, given that the outcome variables (test scores) are bounded, the extremes of the test score variables can be used as the potential counterfactual outcomes to bound the effect of interest without relying on any additional assumptions as shown in Manski (1989)[9]. Even though the students' potential outcomes had they been assigned to a different school shift system (say, the SSS instead of the DSS) are not known, it is known that the outcomes cannot be lower than the lowest possible test score$Y_{\min}$ or higher than the highest possible test score $Y_{\max}$. Therefore, in the absence of any additional information, $E\left[Y|t=0\right]$ can be replaced with $Y_{\min}$ to obtain the lower bound on $E[\mathrm{Y}(t)]$, and with $Y_{\max}$ to obtain the upper bound.

$$\begin{aligned} E[Y^t]_{LB} = E\left[Y|t=1\right]*P(t=1) + Y_{\min}*P(t=0) \\ \leq E\left[Y(t)\right] \leq \\ E\left[Y|t=1\right]*P(t=1) + Y_{\max}*P(t=0) = E[Y^t]_{UB} \end{aligned} \tag{3}$$

10

[9] Note that the WASSCE results analyses use only a dummy that indicates whether a student obtained a passing credit or not. Therefore, the lower and upper bounds are 0 and 1, respectively. For the EGRA results analyses, the minimum and maximum scores obtained by students on each subtask are used to specify the lower and upper bounds.

[10] In the event of a binary outcome variable such as the share of students obtaining a pass or credit, $Y_{\min}$ in Equation [3] has a value of 0 and the equation can therefore be reduced to:

$$E[Y^t]_{LB} = E\left[Y|t=1\right]*P(t=1) \leq E\left[Y(t)\right] \leq \; E\left[Y|t=1\right]*P(t=1) + Y_{\max}*P(t=0) = E[Y^t]_{UB}$$

Applying the same reasoning to $E\,[Y|t\,=\,0]$ and calculating the difference between the lower and upper bounds arrives at Manski's no-assumption or worst-case bounds (Manski, 1989) for the ATE:

$$E[Y^1]_{LB} - E[Y^0]_{UB} \leq {}_{ATE} \leq E[Y^1]_{UB} - E[Y^0]_{LB} \tag{4}$$

These bounds can be quite large; however, they are interesting and informative because any results that are based on different assumptions about the counterfactual are expected to lie within these bounds. The bounds in Equation [4] above can be narrowed by making assumptions about the relationship between attending a school that follows a particular shift system and obtaining a good grade on the individual assessment.

2.1.1 Monotone Treatment Selection

The MTS assumption weakens the ETS assumption (Manski and Pepper, 2000). It assumes that double-shift students have weakly lower education production functions (EPFs) than single-shift students due in part to receiving fewer instructional hours that are not necessarily compensated for by smaller class sizes as one might expect or as is the case in other contexts. Formally, the non-positive MTS assumption states that:

$$E[Y|t\,=\,1] \leq E[Y|t\,=\,0] \tag{5}$$

That is, the EPFs of double-shift students are less than or equal to those of single-shift students. Due to the identification challenges highlighted earlier, the observation that single-shift students tend to have better academic outcomes than double-shift students cannot be interpreted as a causal relationship.

Given the context and background, students in single-shift schools are expected to be more advantaged than students in double-shift schools on several indicators including socio-economic and demographic characteristics. Furthermore, single-shift schools may attract students with higher innate abilities or from more advantaged backgrounds because they are located in urban areas, where students are more likely to have higher household SES. Additionally, single-shift schools might provide a more conducive learning environment, regardless of the shift system itself. Moreover, the concentration of single-shift schools in urban and more developed areas of the country supports expectations that align with the MTS assumption. This assumption excludes the possibility that the characteristics that differentiate single-shift students from double-shift students would impact students' academic performance to such an extent that double-shift students would outperform their single-shift peers if their schools followed the same school shift

system. The MTS assumption therefore increases the lower bound on the mean potential outcome for double-shift students, which can be derived from the following:

$$\begin{aligned} E[Y^t]_{LB-MTS} = E\left[Y|t=1\right] * Pr(t=1) + E\left[Y|t=1\right] * Pr(t \neq 0) \\ \leq E\left[Y(t)\right] \leq \\ E\left[Y|t=1\right] * Pr(t=1) + Y_{\max} * Pr(t=0) = E[Y^t]_{UB-MTS} \end{aligned} \tag{7}$$

The MTS assumption increases the lower bound on the expected academic performance of double-shift students but does not influence the upper bound. It also increases the lower bound on the ATE compared to the most conservative bounds, which effectively reduces the potential negative impact of attending a double-shift school. Consequently, the higher lower bound corresponds to the mean difference in academic performance observed between single-shift and double-shift students. The available data provide some descriptive evidence of this assumption and are used to test its validity.

2.1.2 Monotone Treatment Response

The MTR assumption improves upon the no-assumption bounds by introducing a weak assumption (Manski and Pepper, 2000). It introduces a restriction on the direction of the treatment effect and assumes that student performance, as measured by standardized test scores, is a weakly decreasing function of attending a double-shift school. The MTR assumption further tightens the bounds by reducing the upper bound on the ATE, which was not affected by the MTS assumption:

$$Y(1) \leq Y(0) \tag{8}$$

This means that the potential outcome under the DSS (t=1) for those who attended a single-shift school (t=0) is no less than the potential outcome under the DSS for those who attended a double-shift school. The bounds on the treatment effect of interest for the DSS can be expressed similarly under the MTR assumption as under the MTS assumption. As with the MTS assumption, the MTR assumption makes the bounds on treatment effects tighter than in the worst-case scenario. More specifically, condition [8] implies that this also holds in expectation.

Applying the MTR assumption makes it possible to derive tighter bounds on the ATE. The bounds on the ATE for the DSS are calculated using the same subtraction method as is outlined in the previous section. The upper bound is adjusted downwards because it is assumed that the treatment effect is non-positive. This means that the treatment having a positive effect in the worst-case scenario is ruled out. Under the MTR assumption, the upper bound is given by:

Upper bound MTR $= max(E[Y \mid D = 1] - E[Y \mid D = 0], 0)$

This adjustment ensures that the upper bound is at least zero, which reflects the assumption the treatment effect is non-positive:

$$\begin{aligned} E\left[Y \mid t = 1\right] * Pr[t = 1] + E\left[Y \mid t = 0\right] * \Pr[t = 0]] \\ quad \leq E\left[Y(1)\right] \leq \\ quadE\left[Y \mid t = 1\right] * Pr\left[t = 1\right] + Pr\left[t = 0\right] \end{aligned} \tag{9}$$

In this binary treatment context, it is evident that the upper bound on the ATE is zero and the lower bound corresponds to the observed mean outcome, which represents the worst-case scenario. This aligns with the MTR assumption, which indicates that $E[Y(1)] \leq E[Y(0)]$ and the ATE is non-positive. Consequently, the MTR lower bound remains the same as the worst-case lower bound. In general, the MTR assumption regarding the DSS seems relatively harmless. Given what is known about the DSS, it is difficult to imagine how being in a double-shift school would lead to better learning outcomes than being in a single-shift school.

This assumption suggests that transitioning from the SSS to the DSS would either reduce or, at the very least, not improve student performance on standardized tests. There are compelling reasons to expect the DSS to have a negative impact on academic performance. For instance, double-shift schools may offer fewer instructional hours, worse working conditions for teachers, higher PTRs, and a less-conducive learning environment due to more distractions and disruptions. It is challenging, however, to conceive of plausible scenarios in which attending a double-shift school would improve student performance compared to attending a single-shift school. Nevertheless, it is possible that the type of school shift system may not have a causal effect on academic performance and that the negative associations between the DSS and better test scores that are observed may be attributable to other confounding factors or selection effects. In essence, neither positive nor negative channels are ruled out; however, the DSS's negative channels dominate its positive channels. The non-monotone treatment response allows for a non-linear relationship, i.e., for some double-shift students to have better outcomes than single-shift students. Therefore, it is important that the MTR assumption not dismiss the possibility of zero effect.

2.2 MTS + MTR Assumption

At this stage, it is important to stress that although the MTR and MTS assumptions are related concepts, they are distinct. The MTS assumption pertains to the selection process or the assignment of students to either single-shift or double-shift schools. More specifically, it states that single-shift students have weakly higher mean potential test scores (or test score functions) than double-shift students given the same set of observable characteristics. In other words, the

MTS assumption posits that the factors or characteristics that lead students to be "selected" to be assigned to single-shift schools are positively associated with their potential test scores. This assumption does not necessarily imply a causal relationship but rather acknowledges that there may be unobserved factors or selection effects that differentiate single-shift students from double-shift students.

On the other hand, the MTR assumption pertains to the causal effect the treatment (the school shift system) has on the outcome (student performance or test scores). More specifically, the MTR assumption states that attending a single-shift school would either improve or, at the very least, not diminish student performance on standardized tests compared to attending a double-shift school. In other words, the MTR assumption posits that attending a double-shift school has a non-positive or weakly negative treatment effect on student test scores. It rules out the possibility that attending a double-shift school would lead to better test scores than attending a single-shift school.

The key difference between the two assumptions is that the MTS assumption is related to the selection process and the potential outcomes, whereas the MTR assumption is related to the causal effect the treatment has on the outcome. The MTS assumption pertains to the relationship between the treatment and potential outcomes, while the MTR assumption concerns the direction of the causal effect the treatment has on the observed outcome.

The MTR and MTS assumptions can be combined to further tighten the bounds. The combined MTS + MTR assumption gives:

$$E[Y^t]_{LB-MTS-MTR} = E\left[Y|t=1\right] * Pr(t=1) + E\left[Y|t=1\right] * Pr(t=0) \tag{10}$$

$$\leq E\left[Y(t)\right] \leq$$

$$E\left[Y|t=1\right] * Pr(t=1) + E\left[Y|t=0\right] * P(t=0) = E[Y^t]_{UB-MTS-MTR}$$

2.3 Monotone Instrumental Variable

Instrumental variables (IVs) are used to estimate causal effects when the regressor is endogenous so an instrument that is correlated with the regressor but uncorrelated with the error term (exclusion restriction) is required to obtain consistent estimates (Manski, 1998; Imbens, 2014). In this study, no variable fully satisfies the strict IV conditions due to data limitations. Instead, the weaker monotone instrumental variable (MIV) proposed by Manski and Pepper (2000, 2009) is applied as it requires only a monotonic relationship between the instrument and the outcome.

Manski and Pepper (2000, 2009) argue that the MIV assumption is a less-restrictive version of the standard IV assumption. Unlike an IV, an MIV requires only that the average effect satisfy

a weaker inequality condition, rather than strict equality. This means that an increase (decrease) in the instrument either increases (decreases) the expected outcome or leaves it unchanged but never causes it to move in a different direction. Furthermore, an MIV does not require the traditional exclusion restriction that an IV does or mean independence.

Let V be an ordered set. A covariate v is considered an MIV if it meets the following condition: for every treatment dummy t, any value of w, and any two values $(u_1,\ u_2)\ \in (V * V)$ where $u_2 \geq u_1$, the expected test score given w and v=u_2 is at least as high as the expected test score given w and v=u_1. In other words,

$$E\left[y(t)\middle|\, w, v = u_2\right] \geq E\left[y(t)\middle|\, w, v = u_1\right] \tag{11}$$

To clarify the difference between the IV and MIV assumptions in the context of this study, let v denote a student's household SES. SES may strongly influence whether a student attends a single-shift or double-shift school, which satisfies the IV relevance condition. However, SES likely violates the exclusion restriction because it directly affects learning outcomes through factors like access to resources, parental involvement, nutrition, healthcare, and enriched home environments (Kim et al., 2019; Morrissey et al., 2014). Moreover, using SES as a traditional IV assumes uniform EPFs across SES groups, which is unrealistic.

In contrast, SES qualifies as an MIV since it satisfies the monotonicity assumption: children with lower household SES are slightly more likely to perform poorly than those with higher household SES. Similarly, using the PTR as an IV requires assuming identical EPFs regardless of class size, alongside relevance and exclusion restrictions. When the PTR is used as an MIV, the only requirement is that students in smaller classes have weakly higher EPFs than those in larger classes, which is a plausible and less-restrictive assumption.

The MIV bounds refine the initial expected outcome estimates by narrowing the range of possible values. The lower bound is set by identifying the highest minimum expected outcome among data points where the variable is below a cutoff, while the upper bound is the lowest maximum expected outcome among points above it. This tightening improves estimate accuracy (see De Haan, 2011; De Haan and Leuven, 2017; Germinario et al., 2022). Cutoffs for estimates are placed at quantiles of the MIV variable distribution. Since MIV estimators can be biased in small samples—often underestimating bound widths—the correction method proposed by Chernozhukov et al. (2013) is applied. This yields half-median unbiased bounds and valid confidence intervals, which enhances the reliability of the ATE estimates[11].

[11] This study makes use of the Stata codes provided by Germinario on his personal website at `https://github.com/grpgerminario/mpclr` to estimate the non-parametric bounds.

2.4 Discussion about the Assumptions

This section provides some descriptive statistics to help assess the validity of the assumptions made before the results are presented. These descriptive statistics are based solely on EGRA data, as the WASSCE data were insufficient to conduct similar analyses.

2.4.1 MTS Assumption

The MTS assumption states that double-shift students are negatively selected, i.e., they are from relatively poorer households and are more likely to have poorer prior educational outcomes. The table below shows the differences in demographic characteristics between single-shift and double-shift students.

Table 1 shows that single-shift students are more likely to come from households with modern essential utilities (gas or electric stove, tap water in compound, indoor bathroom) and have better consumption outcomes, including a higher likelihood of having eaten breakfast or a snack at break time, than double-shift students. These asset variables were used to construct an SES index via principal component analysis (PCA). Overall, the data indicate that single-shift students come from better-off households than double-shift students, as reflected by both asset ownership and consumption habits, though the difference is not statistically significant. Furthermore, in terms of student composition, double-shift students are relatively older than single-shift students, less likely to have previously attended any form of education, and less likely to be currently attending other forms of schooling such as Islamic school. These differences are all statistically significant.

2.4.2 MTR Assumption

The table below provides some descriptive evidence of differences in student characteristics and behaviors that support the hypothesis that double-shift students have weaker EPFs than single-shift students.

Although double-shift schools have more classes than single-shift schools, double-shift classes are significantly larger, which results in higher PTRs. While this may seem very intuitive since higher PTRs are usually a motivating factor for adopting the DSS, this just reflects the high demand for spaces in these schools further justifying the need to implement the DSS. Interestingly, double-shift students tend to be more punctual and less likely to have repeated a grade[12]. Differences also exist in access to learning resources, student effort, and parental involvement. Parents of single-shift students are more engaged, as indicated by greater awareness of their child's academic performance.

[12] The space constraints evidenced by the large class sizes could potentially explain why double-shift students are less likely to repeat a grade.

Table 1: Difference in household socio-economic characteristics by school shift system (SSS vs. DSS)

	Single-Shift System	Double-Shift System	Difference in Means
Electricity	0.28	0.30	-0.03
Refrigerator	0.25	0.25	-0.01
Television	0.52	0.50	0.02
Video or DVD player	0.39	0.38	0.01
Radio	0.87	0.89	-0.02
Gas or electric stove	0.28	0.24	0.04**
Bicycle	0.81	0.80	0.00
Motorcycle/scooter	0.29	0.36	-0.08***
Car/pickup/Jeep/tractor	0.25	0.24	0.01
Tap water in the compound	0.28	0.24	0.05**
Bathroom in the house	0.13	0.10	0.03**
Mobile phone	0.97	0.96	0.00
Fixed telephone line	0.05	0.04	0.01
Had a meal this morning	0.70	0.66	0.04*
Had a snack at break time	0.85	0.81	0.03**
Socio-economic status (PCA)	0.04	-0.06	0.09
Previously attended any form of education	0.72	0.64	0.07***
Currently attending Islamic school	0.59	0.55	0.04*

Notes: Source: Author's calculations based on 2016 EGRA data. The values represent the mean share of students whose household has access to assets and their consumption patterns. The asterisks indicate the statistical significance of differences between the two groups (= 1%, ** = 5%, and *** = 10%). The analysis is based on a sample size of 1,305 double-shift students and 874 single-shift students.*

Teacher characteristics and teaching practices also vary: double-shift schools have fewer female teachers (31%, vs. 43% for single-shift schools), which means fewer role models for girls. Additionally, teachers in double-shift schools have less overall teaching experience as well as less grade-specific teaching experience. They are also less likely to assign homework or provide feedback, likely due to larger class sizes and time constraints from teaching multiple shifts. As for school facilities, double-shift students are less likely to have access to a school library, although book borrowing rates do not differ significantly between double-shift and single-shift students. Overall, these findings support the hypothesis that double-shift students have weaker EPFs than single-shift students. When combined, the evidence suggests that the DSS generally provides lower-quality schooling than the SSS.

Table 2: Difference in student effort and parental involvement by school shift system (SSS vs. DSS)

	Single-Shift System	Double-Shift System	Difference in Means
Pupil–teacher ratio	35.12	38.98	-3.86***
Anyone read aloud to you at home	0.63	0.53	0.09***
Practice reading aloud to someone at home	0.60	0.53	0.08***
Studied outside school last week	0.47	0.46	0.01
Ever studied last week with classmates	0.49	0.52	-0.02
Missed any school days last week	0.35	0.34	0.01
Parent aware child did not do well in school	0.71	0.70	0.01
Parent aware child did well in school	0.82	0.77	0.04*

Notes: Source: Author's calculations based on 2016 EGRA data. The values represent the mean share of students whose household has access to assets and their consumption patterns. The asterisks indicate the statistical significance of differences between the two groups (= 1%, ** = 5%, and *** = 10%). The analysis is based on a sample size of 1,305 double-shift students and 874 single-shift students.*

2.4.3 MIV Assumption

The density plot checks in Figure 4 below confirm the monotonicity assumption regarding the MIV considered and student performance: students from higher socio-economic backgrounds generally perform slightly better than their peers from lower socio-economic backgrounds[13].

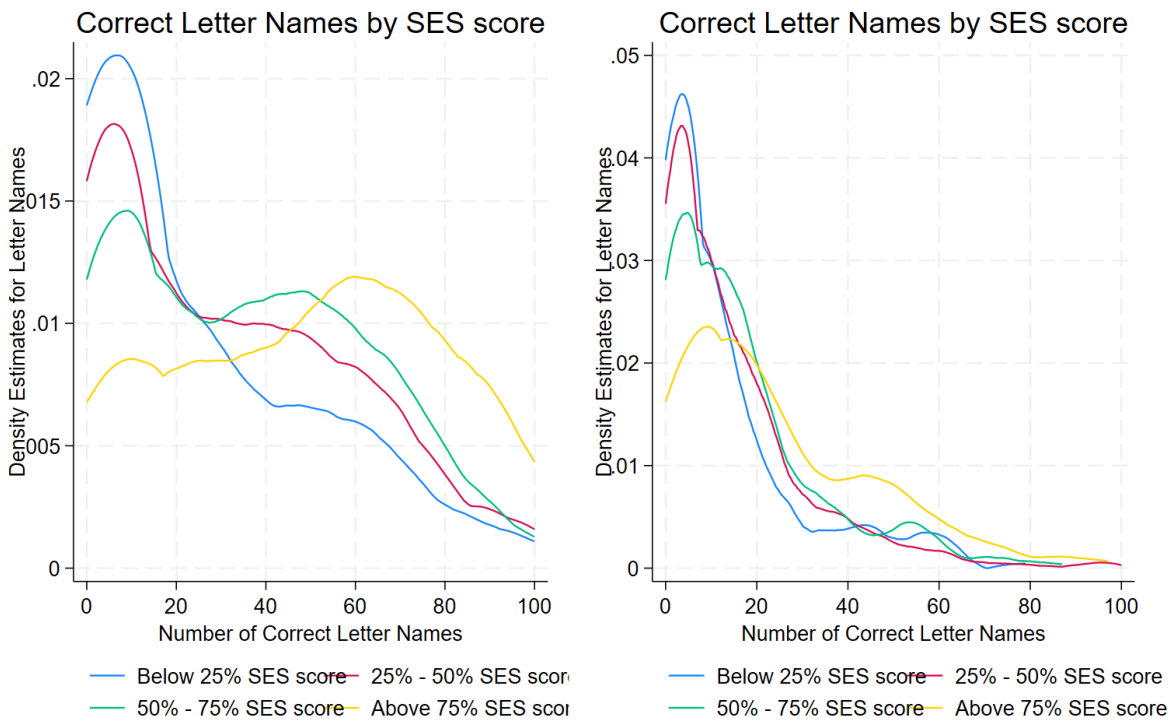
[13] The SES index is based on PCA.

Table 3: Difference in teacher characteristics and teaching practices by school shift system (SSS vs. DSS)

	Single-Shift System	Double-Shift System	Difference in Means
Share of female teachers	0.43	0.31	0.11***
Years of teaching experience	5.74	5.15	0.59*
Years of teaching experience in current grade	2.38	1.87	0.51***
Qualified teacher	0.64	0.60	0.04*
Unqualified teacher	0.06	0.08	-0.02*
Trainee teacher	0.30	0.32	-0.02
Does your current teacher ever practice letter sounds with you?	0.94	0.91	0.03*
Do you ever practice reading aloud to your class?	0.80	0.80	0.00
Does your teacher ever read aloud to you?	0.93	0.90	0.03**
Do you teach the children the names of alphabets/letters?	0.73	0.82	-0.09***
Do you teach the children letter sounds?	0.96	0.98	-0.02*
Do you teach the children common sounds?	0.95	0.95	0.01
Do you read short stories aloud to the children?	0.89	0.92	-0.03*
Do you have the children read aloud to you?	0.93	0.98	-0.05***
Do you give the children homework?	0.98	0.95	0.04***
Do you give feedback after marking an assignment?	0.98	0.99	-0.01
Did you receive any training on how to assess reading?	0.51	0.57	-0.06**
Did you receive any training on how to assess comprehension?	0.46	0.50	-0.05*
Do you have a school library?	0.74	0.62	0.12***
Do students borrow books from the library?	0.44	0.47	-0.03
Are books allowed to be taken from the library?	0.34	0.50	-0.16***

Notes: Source: Author's calculations based on 2016 EGRA data. The values represent the mean share of students whose household has access to assets and their consumption patterns. The asterisks indicate the statistical significance of differences between the two groups (= 1%, ** = 5%, and *** = 10%). The analysis is based on a sample size of 1,305 double-shift students and 874 single-shift students.*

Figure 3: Distribution of correct letter names and sounds by SES score



Notes: Source: Author's calculations. These are kernel density plots.

3 Results

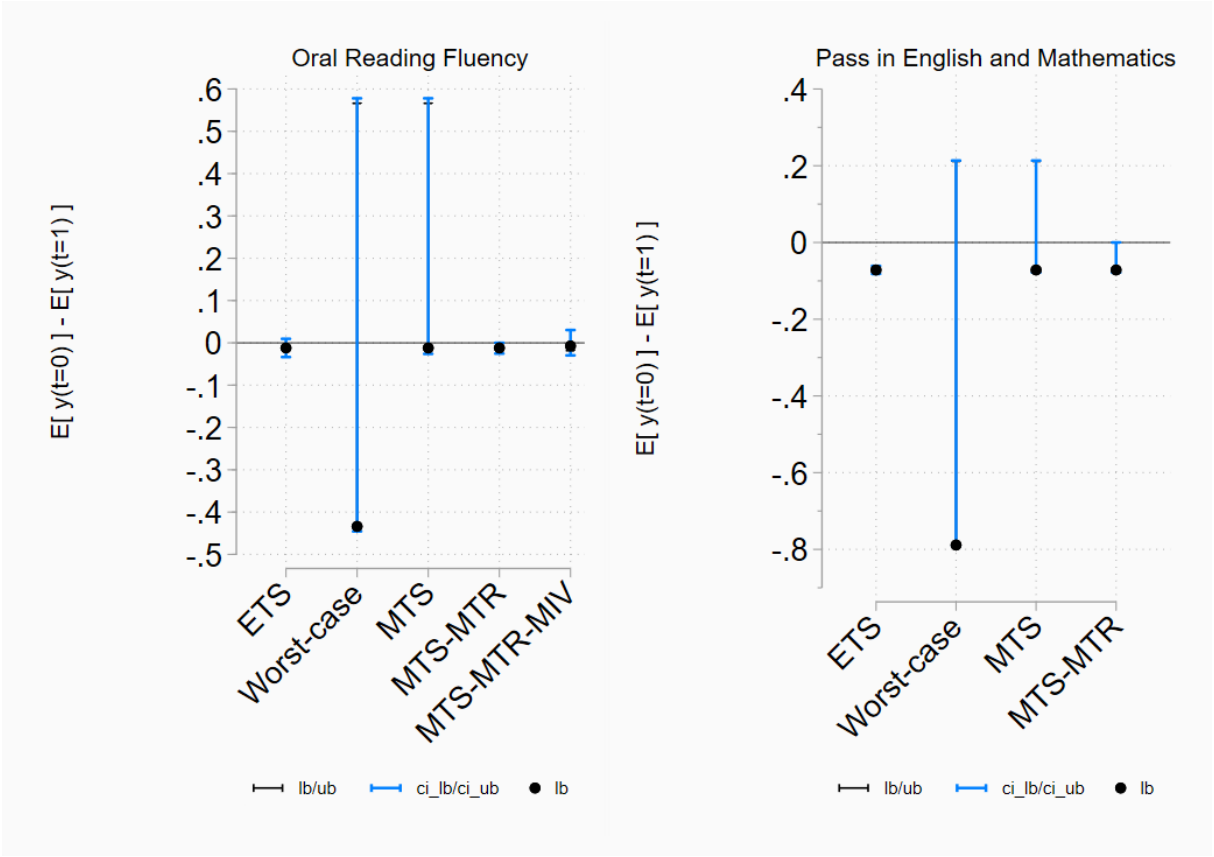
Previous studies suggest there is a strong negative relationship between the DSS and learning outcomes. In order to assess causality, this analysis first examines the unconditional mean difference under the strong ETS assumption—that school shift assignment is random—and compares it with the non-parametric bounds. Since ETS ignores selection bias, it likely overstates the DSS's negative effect (if any). Thus, the true impact is expected to be smaller than it is estimated to be under that assumption. The ETS results are included in the main analysis for comparison purposes.

3.1 Main Findings

Figure 5 shows the effect attending a double-shift school has on standardized ORF scores from the EGRA and the probability of passing both English and Mathematics in the WASSCE. The ETS estimates indicate that primary school students in public double-shift schools score 0.12 standard deviations lower on ORF than their peers in public single-shift schools. Similarly, the ETS estimates show that high school students in private double-shift schools are about

7.2 percentage points less likely to obtain a passing grade in both English and Mathematics than their peers in private single-shift schools.

Figure 4: Effect the DSS has on (a) ORF scores and(b) the probability of obtaining a pass in both English and Mathematics



Notes: Source: Author's calculations based on available data. The graphs show the bounds on the average causal effect that attending a double-shift school has on the standardized ORF subtask (left) and on the probability of obtaining a pass in both English and Mathematics (right). The vertical axis of each graph represents $E[Y|t = 0]$-$E[Y|t = 1]$. *The bars in the graphs indicate the bound and confidence interval estimates for the effect, except for the point estimate using ETS.*

The no-assumption (worst-case) bounds suggest that attending a public double-shift school at the primary level may reduce a student's standardized ORF score by as much as 0.43 standard deviations compared to peers in public single-shift schools at the same level. Similarly, attending a private double-shift school at the high school level is associated with a reduction of approximately 79 percentage points in the probability of passing both English and Mathematics compared to peers in private single-shift schools at the same level. Applying the MTS assumption—that students in double-shift schools are negatively selected and thus have lower average potential outcomes than those in single-shift schools—increases the lower bound on the treatment effect without affecting the upper bound. Under the MTS assumption, the estimated negative effect on standardized ORF scores diminishes substantially, to approximately 0.012 standard deviations,

and the reduction in probability of passing both English and Mathematics is reduced to around 7.2 percentage points.

Also incorporating the non-increasing MTR assumption, which rules out any increasing effect of the DSS conditional on covariates, tightens the bounds considerably by setting the upper bound on the ATE to zero. Under the combined MTS + MTR assumption, the estimated effect on standardized ORF scores is tightly bounded between -0.012 and 0 standard deviations, while the effect on the probability of passing both English and Mathematics is constrained to between -7.2 and 0 percentage points. Incorporating the MIV assumption, which asserts that student performance increases monotonically with SES, further refines these bounds and narrows the estimated effect on standardized ORF scores to between -0.018 and -0.007 standard deviations[14]. The true causal effect the DSS has on test scores lies within the MTS + MTR + MIV bounds for foundational literacy in public primary schools and within the MTS + MTR bounds for private high schools.

3.2 Additional Results

Examining additional outcome variables beyond the standardized ORF score and the probability of passing both English and Mathematics yields consistent findings, as shown in Table 4. For example, primary school students in public double-shift schools score up to 0.03 standard deviations lower on the familiar word subtask and 0.009 standard deviations lower on the letter sound subtask than their peers in public single-shift schools. Likewise, high school students in private double-shift schools are approximately 6 percentage points less likely than their peers in private single-shift schools to obtain five credits including English and Mathematics in the WASSCE. Although the DSS's effect is negative at both the foundational and high school levels, its magnitude remains modest.

To examine whether the impact of attending a double-shift school varies by gender in public primary schools, Table 5 presents the MTS + MTR + MIV bounds estimated for boys and girls separately. The results indicate that the DSS's negative effect on standardized ORF scores appears to be more pronounced for girls, whose lower bound is -0.027 standard deviations, than boys, whose lower bound is -0.006 standard deviations. Despite this difference, the bounds for both genders include zero, which implies that the possibility of no effect for either group cannot be conclusively rejected.

Disaggregation by grade level reveals that students in Grade 1 are disproportionately affected by the DSS compared to students in Grades 2 and 3, as reflected by their standardized

[14] Due to WASSCE data limitations, it was not possible to find a valid WASSCE-related MIV for the analysis. Using the PTR or the number of exam takers per year proves uninformative, and testing for weak stochastic dominance yields inconclusive results. Density plots using these variables also show substantial overlap in performance across class sizes.

Table 4: Additional results regarding the DSS's effect

Variable	Method	Lower Bound	Upper Bound	SE Lower Bound	SE Upper Bound	CI Lower Bound	CI Upper Bound	Bias Lower Bound	Bias Upper Bound
Familiar Words	Worst-Case	-0.437	0.563	0.009	0.009	-0.449	0.575	.	.
	MTS + MTR + MIV	-0.003	-0.031	0.011	0.031	-0.029	0.039	0.001	0.031
Letter Sounds	Worst-Case	-0.442	0.558	0.008	0.008	-0.452	0.568	.	.
	MTS + MTR + MIV	-0.009	-0.009	0.008	0.023	-0.022	0.029	0.000	0.009
Five Credits Including English and Mathematics	Worst-Case	-0.854	0.146	0.001	0.001	-0.856	0.148	.	.
	MTS + MTR	-0.057	0.000	0.004	0.000	-0.062	0.000	.	.
Five Passes Including English and Mathematics	Worst-Case	-0.790	0.210	0.002	0.002	-0.792	0.212	.	.
	MTS + MTR	-0.055	0.000	0.005	0.000	-0.062	0.000	.	.

Notes: Source: Author's calculations.

ORF scores. Whereas the lower bounds for Grades 2 and 3 are -0.010 and -0.008, respectively, the lower bound for Grade 1 is -0.026, which indicates a more substantial potential negative impact. It is important to note that Grade 3 students take the National Assessment Test exam, which may prompt increased investment in or resource reallocation to this cohort. Such targeted support could mitigate the adverse effects of the DSS and thus result in a comparatively smaller estimated impact being observed for Grade 3 students.

Table 5: EGRA Subsample Analyses

Subsample	lb	ub	ci_lb	ci_ub	se_lb	se_ub	bias_lb	bias_ub
Female	-0.027	0.031	-0.046	0.047	0.015	0.013	0.005	0.000
Male	0.006	0.058	-0.018	0.078	0.019	0.015	0.005	0.000
Grade 1	-0.026	0.000	-0.040	0.002	0.011	0.001	0.003	0.000
Grade 2	-0.010	0.033	-0.032	0.052	0.017	0.015	0.002	0.000
Grade 3	-0.008	0.107	-0.046	0.135	0.029	0.022	0.014	-0.003

Notes: Source: Author's calculations. The dependent variable is the standardized ORF score, and the results presented are the MTS + MTR + MIV bounds with their corresponding confidence intervals and standard errors.

Table 6: WASSCE Subsample Analyses

Subsample	Variable	lb	ub	ci_lb	ci_ub	se_lb	se_ub
Region 1	Pass in English and Mathematics	-0.161	0.000	-0.174	0.000	0.010	0.000
Region 1	Five Credits Including English and Mathematics	-0.124	0.000	-0.133	0.000	0.007	0.000
Region 2	Pass in English and Mathematics	0.011	0.000	-0.102	0.000	0.009	0.000
Region 2	Five Credits Including English and Mathematics	0.012	0.000	-0.005	0.000	0.004	0.000
Full sample	Pass in English	-0.023	0.000	-0.035	0.000	0.009	0.000
Full sample	Pass in Mathematics	-0.119	0.000	-0.129	0.000	0.008	0.000

Notes: Source: Author's calculations. The dependent variables are listed in the Variable column, and the results presented are the MTS + MTR + MIV bounds with their corresponding confidence intervals and standard errors.

To further investigate the DSS's impact, its effects on the probability of passing English and Mathematics were disaggregated by subject. The analysis reveals that the DSS exerts a more pronounced negative effect on Mathematics outcomes than English outcomes. More specifically, under the ETS assumption, attending a double-shift school is associated with a 2-percentage

point reduction in the probability of passing English and a substantially larger 12-percentage point reduction in the probability of passing Mathematics.

Applying the worst-case (no-assumption) bounds yields considerably wider intervals, which reflects the uncertainty that is inherent when fewer identifying assumptions are imposed. Under these bounds, the maximum estimated reduction in the probability of passing English is 51 percentage points, and Mathematics, 59 percentage points, which indicates that in the absence of additional assumptions, the DSS's adverse impact could potentially be substantial. However, when the MTR and MTS assumptions are incorporated, the bounds narrow significantly. These assumptions increase the lower bound and reduce the upper bound, and effectively exclude the possibility of the DSS having a positive effect on academic achievement. As is shown in Table 6, the most restrictive bounds indicate that the DSS reduces the probability of passing English by up to 2.3 percentage points and Mathematics by up to 11.9 percentage points.

A regional analysis focusing on Regions 1 and 2 reveals notable heterogeneity in the estimated effects. In Region 1, the tightest bounds suggest that the DSS reduces the probability of passing English by approximately 16 percentage points. In contrast, in Region 2, the DSS's estimated effect is marginally positive, at 1.1 percentage points. A similar pattern emerges for the probability of obtaining five credits including English and Mathematics: in Region 1, the DSS is associated with a reduction of up to 12.4 percentage points, whereas in Region 2, its effect is slightly positive, at up to 1.2 percentage points.

Overall, these findings indicate that the DSS's negative effects are more pronounced for Mathematics than for English and that the magnitude, and even the direction, of the effect can vary substantially from one region to the next.

3.3 Conclusion

The effect the DSS has on learning outcomes has generally been assumed to be negative. Anecdotal evidence suggests both parents and policymakers perceive the DSS to have a negative impact. In some countries, the DSS has already been abolished completely, while in others, governments have made it a key priority to reduce their use of it or eliminate it entirely. However, empirical evidence supporting its abolishment is limited, especially when considering the cost implications. In resource-constrained economies, the DSS increases access to education with minimal additional cost and may reduce class size, which allows for more personalized teaching and makes it easier to justify expenditures on resources like libraries and laboratories. Despite these potential benefits, blame for poor learning outcomes is sometimes placed on the DSS instead of other issues. The lack of a clear identification strategy is a key challenge when it comes to empirically establishing causality and estimating the magnitude of the causal effect, and it has limited the empirical literature on the DSS's effect to date.

This study addresses the identification challenges that are inherent in estimating the effect the DSS has on learning outcomes by employing a non-parametric bounds analysis approach. This approach, which is relatively underexplored in the context of educational research, provides a range of plausible treatment effects based on a set of weak and partially testable non-parametric assumptions. Furthermore, this study estimates the bounds on the ATE without relying on the assumption the DSS has a linear and homogeneous effect.

This paper confirms that the double-shift schooling system negatively impacts learning outcomes at both the foundational and high school levels, as evidenced by performance on the EGRA standardized literacy assessment in public primary schools and the WASSCE in private high schools. A back-of-the-envelope calculation suggests that converting all private double-shift high schools to single-shift ones—with additional classrooms and teachers—would increase the pass rate in English and Mathematics in private high schools from approximately 20% to 21.5%, a marginal 1.5-percentage point improvement. Similarly, it is estimated that converting all public double-shift primary schools to single-shift ones would improve standardized ORF scores in public primary schools between 5% and 13%. While the adverse effects of the DSS are statistically significant, their magnitude is relatively modest compared to the substantial benefits that are provided by the increased educational access that the DSS affords.

Notably, this study reveals that the DSS exerts a more detrimental effect on girls than on boys at the primary level, which underscores the need for more targeted and effective engagement strategies during after-school programs in double-shift settings. Furthermore, the attenuation of adverse effects that is observed from Grade 1 to Grade 3 suggests that early impacts may largely reflect the strong foundational skills acquired through private schooling or early childhood development programs prior to Grade 1. Regional disparities in outcomes are also anticipated, given the variability in student and teacher quality as well as students' household socio-economic characteristics, which partially explains the DSS's effects being more pronounced in Region 1 than Region 2.

A key finding that warrants emphasis is that, unlike the substantial and significant negative effects that are observed for private double-shift high schools, there is comparatively weaker evidence that students in public double-shift primary schools perform worse than their counterparts in public single-shift schools. Consequently, the main implication of this study is that transitioning from the DSS to the SSS under current conditions may not necessarily yield significant improvements in foundational learning outcomes. This distinction is particularly important because the schools included in the evaluation at the foundational level are public schools, while those at the high school level are all private schools. This is largely due to the absence of private primary schools in the sample considered and the fact that almost all the public high schools in the sample followed the DSS. While many policy efforts to abolish the DSS are likely to focus

on the public sector, this study highlights that greater gains may be achieved by targeting private high schools.

This study finds that attending a double-shift school has a negative effect on learning outcomes, with variations across subjects, school types, and regions. Furthermore, the DSS appears to have a slightly larger adverse effect on Mathematics than on English at the high school level (Grade 12). At the foundational level, relying on a student's household SES yields tighter bounds on the effect the DSS has on reading assessment performance. While the DSS is found to have a negative effect in most cases, the findings do not generally rule out the possibility that it have null effects. The DSS's negative impact on learning outcomes aligns with concerns raised by scholars and policymakers about potential trade-offs between access to education and educational quality. The variations observed across subjects, school types, and regions suggest that the DSS's effect is not uniform and may be influenced by contextual factors.

Overall, this study contributes to the ongoing discourse on the DSS by providing empirical evidence of its negative effects on student learning, particularly in certain subjects and contexts. However, the findings also underscore the complexity of the issue and the need for nuanced policy decisions that carefully weigh the trade-offs between access and quality while considering potential interventions aimed at addressing the issue of poor learning outcomes.

References

Alberto, I. C., Y. Jiao, and X. Zhang (2021, October). Too hot or too cold to study? The effect of temperature on student time allocation. *Economics of Education Review*, *84*, 102152.

Arceo-Gómez, E. O., R. M. Campos-Vazquez, and C. M. Muñoz-Pedroza (2018). Double-shift high schools and school performance: Evidence from a regression discontinuity design.

Azevedo, J. P., D. Goldemberg, S. Montoya, R. Nayar, H. Rogers, J. Saavedra, and B. W. Stacy (2021, March). *Will Every Child be Able to Read by 2030? Defining Learning Poverty and Mapping the Dimensions of the Challenge*. Policy Research Working Paper. The World Bank.

Barrios-Fernández, A. and G. Bovini (2021, February). It's time to learn: School institutions and returns to instruction time. *Economics of Education Review*, *80*, 102068.

Bray, M. (1989, January). *Multiple-Shift Schooling: Design and Operation for Cost-Effectiveness*. Journal Abbreviation: `http://lst-iiep.iiep-unesco.org/cgi-bin/wwwi32.exe/[in=epidoc1.in]/?t2000=004520/(100)` Publication Title: http://lst-iiep.iiep-unesco.org/cgi-bin/wwwi32.exe/[in=epidoc1.in]/?t2000=004520/(100).

Bray, M. (2008, March). *Double-shift Schooling: Design and Operation for Cost-effectiveness*.

Commonwealth iLibrary.

Cabrera-Hernández, F. (2020, February). Does Lengthening the School Day Increase School Value-Added? Evidence from a Mid-Income Country. *The Journal of Development Studies*, *56*(2), 314–335. Publisher: Routledge. eprint: `https://doi.org/10.1080/00220388.2018.1563680`.

Cygan-Rehm, K., D. Kuehnle, and M. Oberfichtner (2017). Bounding the causal effect of unemployment on mental health: Nonparametric evidence from four countries. *Health Economics*, *26*(12), 1844–1861. eprint: `https://onlinelibrary.wiley.com/doi/pdf/10.1002/hec.3510`.

De Haan, M. (2011). The Effect of Parents' Schooling on Child's Schooling: A Nonparametric Bounds Analysis. *Journal of Labor Economics*, *29*(4), 859–892. University of Chicago Press.

Dominguez, P. and K. Ruffini (2023, July). Long-Term Gains from Longer School Days. *Journal of Human Resources*, *58*(4), 1385–1427. University of Wisconsin Press, Articles section .

Germinario, G., V. Amin, C. A. Flores, and A. Flores-Lagunes (2022). What can we learn about the effect of mental health on labor market outcomes under weak assumptions? Evidence from the NLSY79. *Labour Economics*, *79*(C). Elsevier.

Glewwe, P., C. Siameh, B. Sun, and S. Wisniewski (2021). School Resources and Educational Outcomes in Developing Countries. In *The Routledge Handbook of the Economics of Education*. Routledge. 35p.

Glewwe, P. W., E. A. Hanushek, S. D. Humpage, and R. Ravina (2011, October). School Resources and Educational Outcomes in Developing Countries: A Review of the Literature from 1990 to 2010.

Hanushek, E. A. (2020, January). Chapter 13 – Education production functions. In S. Bradley and C. Green (Eds.), *The Economics of Education (Second Edition)*,
pp. 161–170. Academic Press.

Imbens, G. W. (2014). Instrumental Variables: An Econometrician's Perspective. *Statistical Science*, *29*(3), 323–358. http://www.jstor.org/stable/43288511.

Kea, P. (2007, October). Girl Farm Labour And Double-Shift Schooling In The Gambia: The Paradox Of Development Intervention. *Working Paper Series*, No. 39. Department of Economics, University of Sussex Business School.

Kim, S. W., H. Cho, and L. Y. Kim (2019). Socioeconomic Status and Academic Outcomes in Developing Countries: A Meta-Analysis. *Review of Educational Research*, *89*(6),
–916. https://doi.org/10.3102/0034654319877155.

Linden, T. (2001a). Double-shift secondary schools: Possibilities and issues.

Linden, T. (2001b, August). Double-Shift Secondary Schools: Possibilities and Issues.

Lusher, L. and V. Yasenov (2016). Double-shift schooling and student success: Quasi-experimental evidence from Europe. *Economics Letters*, *139*(C), 36–39. Elsevier.

Manski, C. F. (1997). Monotone Treatment Response. *Econometrica*, *65*(6), 1311–1334. Wiley, Econometric Society.

Manski, C. F. and J. V. Pepper (2000). Monotone Instrumental Variables: With an Application to the Returns to Schooling. *Econometrica*, *68*(4), 997–1010. Wiley, Econometric Society.

Morrissey, T. W., L. Hutchison, and A. Winsler (2014). Family income, school attendance, and academic achievement in elementary school. *Developmental Psychology*, *50*(3),
–753. https://doi.org/10.1037/a0033848.

Nhundu, T. (2001, January). Bray, Mark. 2000. Double-Shift Schooling: Design and Operation for Cost-Effectiveness. *International Review of Education*.

Ovalle-Ramirez, C. P. (2018). Effect of the double school day on the academic performance of Colombian students: An empirical analysis to inform the full day policy. *Education Policy Analysis Archives*, *26*, 81. https://doi.org/10.14507/epaa.26.2990.

Park, R. J., A. P. Behrer, and J. Goodman (2021, January). Learning is inhibited by heat exposure, both internationally and within the United States. *Nature Human Behaviour*, *5*(1), 19–27. Nature Publishing Group.

Pritchett, L. and D. Filmer (1999, April). What education production functions *really* show: A positive theory of education expenditures. *Economics of Education Review*, *18*(2), 223–239.

Rossiter, J., M. K. Abreh, A. Ali, and J. Sandefur (2023, June). The High Stakes of Bad Exams. *Journal of Human Resources*. University of Wisconsin Press, Articles section.

Smart, S. (2023). Phasing Out Shift Schools: More Instructional Hours Linked to Better High-Stakes Test Scores. *China Economic Review*.

Appendix A: Additional tables and figures

The tables below provide summary statistics for the key variables.

Table A1: Summary Statistics, WASSCE Data

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
Number of students per school	12566	191.873	121.156	5	421
Total students per school year	12566	11527.844	1602.982	9481	13806
Number of classes per grade	12450	4.157	2.024	1	9
Class size	12450	46.557	22.68	5	101.333
Number of subjects per student	12566	8.148	1.129	1	9
Double-shift yes	12566	.556	.497	0	1
5 credits incl. English & Mathematics	12566	.061	.24	0	1
Share 5 credits incl. English & Mathematics	12566	4.281	.848	3.359	6.013
% of students with 5 credits per school	12566	.061	.142	0	.601

Table A2: Summary Statistics, EGRA Data

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
Double-shift school	2180	0.401	0.49	0	1
Public	2180	1	0	1	1
Female	2180	0.494	0.5	0	1
Total number of students in grade per school	2152	98.657	120.596	4	659
Pupil–teacher ratio	2147	36.678	13.354	4	195
Number of absentees	2180	10.638	11.923	0	73
Number of classes per grade	2175	2.387	2.145	1	11
Multi-grade class	2178	0.057	0.233	0	1
Ever repeated a grade	2178	0.227	0.419	0	1
Previously attended any form of education	2180	0.686	0.464	0	1
Currently attending Islamic school	2180	0.572	0.495	0	1
Had a meal this morning	2179	0.679	0.467	0	1
Had a snack at break time	2180	0.834	0.372	0	1
Have electricity at home	2178	0.287	0.452	0	1
Tap water in the compound	2176	0.264	0.441	0	1
Have reading books at home	2180	0.579	0.494	0	1
Anyone read aloud to you at home	2180	0.589	0.492	0	1
Practice read aloud to someone at home	2180	0.573	0.495	0	1
Studied outside school last week	2180	0.468	0.499	0	1
Ever studied last week with classmates	2180	0.503	0.5	0	1
Missed any school days last week	2180	0.344	0.475	0	1
Parent aware child did not do well in school	2180	0.703	0.457	0	1
Parent aware child did well in school	2180	0.801	0.399	0	1
Correct letter names per minute	2179	.36	.289	0	1
Correct Letters Sounds per minute	2143	.17	.182	0	1
Correct familiar words per minute	2159	.151	.252	0	1
Correct non-familiar words per minute	2158	.137	.258	0	1
Oral reading fluency	2180	.125	.221	0	1