UNU WIDER

WIDER Working Paper 2024/7

Smart classrooms and education outcomes

Evidence from Rwanda

Aimable Nsabimana,[1] Muthoni Nganga,[2] and
Christine Niyizamwiyitira[3]

February 2024

Abstract: In this study, we explore the impact of a smart classroom (SCM) programme on student performance in science subjects in a high-stakes national exam for middle-high school students in Rwanda. To do this, we leverage plausibly exogenous variations in programme exposure induced by the staggered implementation of the programme across schools and students. Overall, the study finds a positive effect of the programme on student performance. Specifically, the results show that the SCM programme has positive and significant effects on student performance in physics, biology, and geography, albeit small in magnitude. The study, however, did not reveal any effects on mathematics and chemistry. We find larger effects in government-aided schools, for girls, and for younger students. Our results also indicate that while classroom technology can enhance learning, such effects may only be realized after a long exposure period.

Key words: secondary education, smart classrooms, Rwanda

JEL classification: I21, I26, O12

Acknowledgements: We are grateful to the Rwanda National Examination and School Inspection Authority (NESA) for granting access to standardized student grades datasets and to the Rwanda Ministry of Education (MINEDUC) and the Rwanda Basic Education Board (REB) for sharing official documents related to the country's education sector. All errors and views expressed in this paper are those of the authors. They do not necessarily represent the views of UNU-WIDER, Wilfrid Laurier University, or Carnegie Mellon University Africa.

---

[1] UNU-WIDER, Helsinki, Finland, aimable.nsabimana@wider.unu.edu; [2] Wilfrid Laurier University, Waterloo, Canada, muthonian@gmail.com; [3] Carnegie Mellon University Africa, Kigali, Rwanda, cniyizam@andrew.cmu.edu

This study has been prepared within the UNU-WIDER project on 'Academic excellence'.

Information and requests: publications@wider.unu.edu

ISSN 1798-7237 ISBN 978-92-9267-465-6

https://doi.org/10.35188/UNU-WIDER/2024/465-6

Typescript prepared by Siméon Rapin.

United Nations University World Institute for Development Economics Research provides economic analysis and policy advice with the aim of promoting sustainable and equitable development. The Institute began operations in 1985 in Helsinki, Finland, as the first research and training centre of the United Nations University. Today it is a unique blend of think tank, research institute, and UN agency—providing a range of services from policy advice to governments as well as freely available original research.

The Institute is funded through income from an endowment fund with additional contributions to its work programme from Finland and Sweden, as well as earmarked contributions for specific projects from a variety of donors.

Katajanokanlaituri 6 B, 00160 Helsinki, Finland

1 Introduction

While there are observable milestones towards educational achievement in developing countries, there are still questions on how much learning is achieved by students as acquisition of basic competencies remains fairly low (Jones et al. 2014; Filmer et al. 2018; Valente 2019). Gust et al. (2023) find that there are huge gaps in skills acquisition with about 65 per cent of world youth not obtaining basic skills that should enable them to succeed in modern developed economies.[1] The gaps are highest in sub-Saharan Africa, at 90 per cent compared to 24 per cent in high-income countries. For example, among those enrolled in secondary schools in Rwanda, 90 per cent do not have basic skills. This raises the question about what educational resources are required and their effective utilization in order to ensure acquisition of basic skills (Hanushek 2003). Interventions towards improving education attainment may also include provision of incentives that enhance learning by considering heterogeneities across learners or trainees (Duflo et al. 2011; Drexler et al. 2014; Muralidharan et al. 2019).

One intervention that has not received much attention in developing countries is the introduction of technology in classrooms. In part, this is due to the cost of technology which makes it less commonly used in countries facing severe funding constraints. It is only in the last several years that smart classroom[2] technologies have begun to be introduced at the elementary and secondary school level. In this study, we estimate the impact of a smart classroom (SCM) national programme in Rwanda on students' grades in five STEM[3] subjects—mathematics, biology, chemistry, physics, and geography—in a high-stakes national exam in the final year of lower secondary schooling.

The Ministry of Education in Rwanda introduced the SCM programme in 2016 and started rolling it out in lower secondary schools around the country in 2017. Each school receives 51 computers per class, either for two classes if the school has two classrooms available (hence 100 students' and two teachers' computers), or for one class if the school only has one room available. The distribution is non-random since a school receives the computers after verifying that it is connected to the electricity grid or after connecting the school if it is not connected. The computers are connected to the internet and installed with informational materials to aid with class preparations. The computers are to be utilized for computer classes and in teaching other subjects, with the teachers—especially STEM-subject teachers—being encouraged to utilize them to conduct their lessons and in other students' activities such as assignments. Our

[1] See Gust et al. (2023) for a more detailed discussion on basic skills.

[2] Smart classrooms are classes that are enhanced technologically by introducing technology infrastructure, mainly computers, and digital content that provide a substitute or complement to the traditional modes of teaching and learning using textbooks and chalk/white boards. A more detailed discussion of the smart classroom programme in Rwanda is discussed in Section 2.

[3] In full: science, technology, engineering, and mathematics.

data covers six academic years (2015–21) with 772 schools and over 300,000 students in the final year of lower secondary school level who have different months of SCM exposure. The length of exposure varies with the year and month of the programme's introduction in each school and the student's grade level at the time of exposure.

Given the staggered implementation of the SCM programme, we employ a quasi-experimental identification strategy. We take advantage of the exogeneous variation in the students' exposure to the programme that is created by the differences in the year and month when the programme was introduced across schools and the age and grade level of the students at the time of exposure. Using this variation, we estimate the intention to treat (ITT) impact of the programme. We also explore heterogeneous effects across gender and school types as well as possible mechanisms through which the impacts occur.

We find a positive impact of the programme on physics, biology, and geography performance with the grade points increasing by 0.002 to 0.004 standard deviation for every month of exposure to the programme, but nil effect in mathematics and chemistry. However, when we consider the programme's intensity that varies with the exposure period, the impact is almost nil in the first ten months of exposure but positive and increasing after 11 months. After 21 months, the programme has a positive and statistically significant impact on all the five subjects.

The baseline results show that female students' scores are lower than for their male counterparts in all the subjects. We find that female students see a larger performance boost from the SCM programme than the male students, leading to a reduction in the gender gap in performance. The gender gap continues to narrow with increased exposure to the programme. This higher gain for female students may be resulting from the fact that they start at much lower scores than male students. Additional results include the SCM programme's effect across different school types including public, private, and government-aided schools that are privately managed but receive government funding. We find that government-aided schools benefit more from the programme than other schools, suggesting the importance of public–private partnerships in education provision.

The use of technology in class is likely to change class interaction; hence smart classrooms likely impact on student learning through changes in instruction that can either be a cause of class disruption or may trigger efficiency in learning (Muralidharan et al. 2019). Other benefits of smart classroom integration in learning include enhancement of student-centred learning (Chen and Tsai 2021), fostering self-guided learning (Karabenick 2011; Derksen et al. 2022), and increased interaction inside and outside of physical classrooms. Recent literature also shows that education technology infrastructure can be useful in circumstances that necessitate learning from different locations, such as during the COVID-19 pandemic (König et al. 2020; Grek and Landri 2021). However, successful integration of technology in learning may be hindered by several factors including teachers' negative perceptions on technology use and inadequate teachers' training (Ghavifekr and Rosdy 2015; König et al. 2020).

Our study contributes to the literature on classroom technology and learning in several ways. First, we answer a policy-relevant question on the impact of a national programme that introduced technology in classrooms on the academic achievement of learners in a developing country. To the best of our knowledge, this is among the first studies on the impact of a massive national programme that tries to integrate a SCM programme with other school programmes in the region. Evaluations of large-scale government programmes such as the Rwanda SCM programme are key to informing public policy on education. Secondly, the staggered roll-out of the SCM programme allows us to have a strong identification strategy to estimate the impact of the programme on students' academic achievement. Thirdly, the data allows us to estimate the impact of the programme after several years of its implementation, as such an evaluation is often not possible for field experiments conducted over a short period. We also contribute to the literature on the relationship between classroom technology and learning outcomes at the secondary school level.

A closely related study to ours (given that the implementation almost replicates a national-level implementation) is one by Cardim et al. (2023), who conducted a randomized control experiment in Angola to estimate the impact of a computer-assisted learning international programme targeted at vulnerable primary school students in developing countries. After about 11 months of exposure to the programme, they find an improvement in test scores for subjects that are targeted by the programme, improved teacher class preparation, and increased student engagement. Other experimental studies, all conducted at the primary school level, include Bai et al. (2023), who find that an online computer-assisted learning tutoring programme improves English test scores for fifth-grade students in China. Similar to the results in our study, Rouse and Krueger (2004) find very dismal improvements in reading resulting from a randomized experiment on computer use in classrooms in America, while Bando et al. (2017) find that replacement of text books with laptops did not improve elementary students' test scores after one year of the experiment in Honduras. They however warn that this does not rule out longer-term effects, which is consistent to our findings that a longer exposure period is likely to produce positive impacts even on subjects where the impact was not statistically different from zero after a few months of the exposure. We look at the effects of SCM after one year and similar to these studies, we find that the effects after that period are almost nil. However, our study allows us to look at effects after two and three years, and we find that the effects increase with the increase in exposure time. In addition, all these studies focus on primary school achievement while our study focuses on the secondary school level.

Studies that look at the impact of computer technologies and education outcomes at the secondary school level include Muralidharan et al. (2019), who examine the impact of an after-school instruction programme on lottery winners in middle school in India. They find that the lottery winners exposed to a software with interactive instructions such as games and other activities scored 0.37sd and 0.23sd higher in maths and Hindu language, respectively, compared to students in the control group. The authors posit that the positive effects of exposure to the programme came from the change in instruction mode that allows for teaching to be tailored to each student. Derksen et al. (2022) also use a randomized experiment to evaluate the impact of giving access to internet through Wikipedia for about six months on the test scores of students in Malawi. Similar to our study, they find a positive impact of technology access on some subjects and nil effect on others. Specifically, access to the internet closes the achievement gap in English and biology between high and low achievers by improving the scores of the low achievers but has no effect in mathematics and other science subjects. The programmes in these studies are after/extra school programmes, which differs from the programme of focus in our study that integrates traditional teaching methods with the SCM-aided teaching approaches and is also rolled out at the national level.

There are also some studies that have used non-experimental methods to analyse the relationship between information technology and learning and shed light on possible mechanisms through which the impact of classroom technologies on learning may arise. In a case study in Nigeria, Lawrence and Tar (2018) found that both institutional barriers—such as lack of technical support or infrastructure limitations—and teacher-level barriers—such as resistance to change from traditional teaching methods—hinder the benefits that would otherwise be realized with the implementation of ICT in learning. In addition, the development of a curriculum that integrates ICT or the participation in programmes that train the teachers on such integration are key in enhancing efficiency in the use of ICT in class (Yildirim 2007; Lawrence and Tar 2018; Bowman et al. 2022). Moreover, for successful integration of ICT in teaching, such integration may need to be complemented with changes in teaching models (Sangrà and González-Sanmamed 2010). We evaluate some of these mechanisms. Specifically, we look at infrastructure limitations, namely the student-computer ratio in schools.

Most of the reviewed literature is based on experiments on programmes that are rolled out for one year. This does not allow for evaluation of impacts beyond one year and comparison of results for short-term versus long-term exposure periods. In addition, while experiments are useful in answering most impact evaluation questions, the results from such experiments may not be replicated once the intervention is scaled up, hence raising the question of external validity. This is perhaps due to government inefficiencies or bureaucratic implementation procedures (Bold et al. 2018; Vivalt 2020). Our study fills this gap by evaluating the impact of a national SCM programme—an actual scaled-up programme—in a developing country environment for the first five years of its implementation.

The rest of the paper is structured as follows. Section 2 describes the education system in Rwanda and the SCM programme. Section 3 presents our identification strategy and data sources. We introduce and discuss our results in Section 4. We present the heterogeneity analysis and mechanisms in Sections 5 and 6, respectively. Section 7 concludes the paper.

2 Context

2.1 Basic education in Rwanda

Rwanda has a 3-6-3-3 basic education system, comprising three years in pre-primary (kindergarten) school, six years of primary school and six years of secondary school. Secondary schooling is divided into two, three years of lower/ordinary level and three years of upper/ advanced level. After completion of the lower level, students —through national exams as shown by Table 4— may decide to transit to general education (GE), technical & vocational education (TVE), or teacher training center(TTC). After three years into upper secondary school, students will again take other national exams, and the results will be used as the metric for progression to be admitted to the university for a bachelor's degree. In the final year of primary school (grade 6), students undertake a mandatory national exam in five subjects (mathematics, science, social studies, Kinyarwanda, and English). Although all sixth graders are eventually promoted into the middle schools, best performing students in the national exam are automatically given places in boarding schools while the low-performing students are promoted into the same schools they attended primary schooling in what is commonly known as twelve years of basic education (12YBE). After completing three years in lower secondary school, students sit another mandatory national exam in nine subjects (mathematics, physics, biology, chemistry, geography, history, English, Kinyarwanda, and entrepreneurship) also used to determine progression into higher secondary schools. The National Examination and School Inspection Authority uses the student's performance and individual choices to allocate appropriate programmes in upper high school. The students can either be selected for studies in general education, technical and vocational education training, or teaching training education.

Following the implementation of universal primary education in Rwanda since 2003, the government provides free and compulsory education in all public schools up to the end of secondary education. Of all secondary school students, 35.91 per cent attends public schools, while 57.84 per cent attends government-aided/subsidized schools and 6.23 per cent private schools.

2.2 Smart classroom programme in Rwanda

Educational reform. In 2017, the government of Rwanda launched a seven-year government programme (2017–24) known as the Rwanda National Strategy for Transformation (NST1). The programme was aligned to pick up where the Economic Development and Poverty Reduction Strategy (EDPRS 2) left off and continue to accelerate the national transformation and economic growth (Primature 2017). The NST1 outlined a list of goals that the country aimed to achieve by 2024.[4] With this new strategy, the country's public policy was set to develop and 'transform the Rwandan citizens into skilled human capital' (MINEDUC 2017), able to compete in a global environment. One of the main goals was to transform education by integrating ICT into teaching and learning from an early stage. In light of this goal, the country adopted a new education sector strategic plan (ESSP) for the period 2018/19–23/24 (MINEDUC 2016, 2017). Under the new ESSP, the use of ICT would be given special attention in order to transform teaching and learning through the improvement of quality across all education systems.

The Ministry of Education launched the SCM programme in 2016 as part of the ICT education policy, with the actual roll-out to schools in 2017 and a five-year integration plan. The programme aims to improve teaching and learning by integrating it with traditional teaching methods.

The introduction of SCM programme involved first ensuring that the physical infrastructure (classrooms and access to electricity by beneficiary school) required to support computer classrooms was available in a school. The computers were then provided in two classrooms per school, each class holding 50 students' computers and one teacher's computer. To facilitate learning, the computers were connected to the internet and installed with relevant documentation to guide the teachers while preparing lessons. There were no specific software programmes installed for each subject, so the programme is not equivalent to computer-aided learning but instead provides a platform for teachers to incorporate pedagogical methods supported by ICT, such as the development of research-based assignments. Before a smart classroom was created in the school, the school teachers and school managers were trained on how to use the ICT resources for both course preparation and teaching processes. The SCM programme was rolled out into phases due to limited resources. It started with 425 schools in January 2017 and by January 2021, around 772 schools had benefited the SCM programme, as indicated in Figure 6. By 2021, Rwanda had around 1,467 secondary schools, meaning that in the period of four years, more than 52 per cent of total middle schools had access to SCM. Further, the introduction of the SCM programme was also associated with the distribution of projectors and One government Network (OGN) with 10 megabits per second (10Mbps), enabling internet access in the two smart classrooms of each school. Every class-cohort is required to have a weekly specific time for an ICT course. Aside the ICT courses, each teacher is allowed to use the lab, especially in STEM subjects, to teach students how they can use the technology to learn quickly and effectively. The students are also given homework and assignments that require

[4] The NST1 was introduced after President Paul Kagame overwhelmingly won the presidential election of 2017, and the programme outlines the new government's strategic economic plans. For more information, see: https://www.primature.gov.rw/news-detail/pm-ngirente-presents-7-year-government-programme-to-parliament and https://faolex.fao.org/docs/pdf/rwa206814.pdf.

them to use the lab to work on the solutions. In Figures 2 and 3, we show the Rwandan smart classroom seating arrangements and actual students during a class session.

2.3 Theory of change

In line with the ICT-in-education policy in Rwanda, MINEDUC (2016) outlines several policy goals, objectives, and intended outcomes as illustrated in Figure 1. These include but are not limited to the expansion of access to education and improving the quality of education to ensure that learners acquire skills that are relevant in the labour market locally and internationally. To achieve these goals, it is crucial, first, to integrate ICT into teaching and learning at all education levels and, second, to provide capacity building for educators. Together, achieving the two objectives will lead to the development of competent and relevant tech-savvy professionals in all growth industries. To achieve these objectives, there are several required investments in infrastructure as well as in human capital. These are investments in electricity connectivity in schools and other learning centres, acquisition and distribution of digital devices for example through the SCM programme, development of curriculum or adaptation of curriculum to ICT in teaching and learning, teachers' training, and regular support and maintenance of smart classrooms including periodic pedagogical inspections to ensure quality assurance.

The above policy goals, objectives, and channels target several outcomes. These are (1) enabling access to education for all, (2) improving teachers' skills in order to promote change and ensure quality, (3) preparing students for the 21st century and the globe. This will, as mentioned earlier, eventually lead to the transformation of Rwandan citizens into skilled human capital for the socio-economic development of the country(MINEDUC 2017).

3 Estimation strategy and data

3.1 Empirical strategy

Because the programme roll-out was not random across schools, the pre-post estimations between beneficiary and non-beneficiary schools are unlikely to yield the causal impact of the programme. We therefore cannot rely on a comparison of treated to untreated schools. To identify the effect of the SCM programme on education outcomes, we rely on variation in treatment timing among lower secondary schools and student age at the time of the first exposure to the programme. Therefore, instead of deriving the average treatment effect on treated (ATT), this study identifies the effect of potential SCM exposure on student performance using an intention to treat (ITT) set-up. This is important in this context as we derive the overall effect in the full population of the beneficiary cohorts.

We, therefore, leverage the plausible exogenous variation in (students') exposure to the programme, jointly determined by the students' age at the time of SCM implementation and their age at the time of sitting national exams across schools. A similar approach was taken by Chakraborty and Jayaraman (2019). This implementation process (Figure 6) created variations in the intensity of exposure across schools and student cohorts. Furthermore, basic education in Rwanda is highly associated with age. The official lower secondary school age is between 12 and 15 years.[5]. Thus, combining the variations in the implementation of the SCM programme across schools and variations in the grade (age) levels at the time of implementation[6], we compute, for each student cohort, the cumulative number of 'school months' students were exposed to the programme in the respective schools. For example, two students, Baba and Keke are of the same student cohort in the first year of lower secondary school in 2017. Assuming that the school of the first student (Baba) was part of the 'early beneficiaries' (January 2017) while the school of the second student (Keke) was in the 'middle beneficiaries' category (January 2019). When participating in the national exam after completing three years of ordinary school (November 2019), the first student's exposure to the programme would be 30 months (which is the maximum he could have had), while the cumulative exposure to the SCM programme for the second will be 10 months. Now assume that two students, Pete and Molly, are in the same school that becomes a SCM beneficiary in March 2017. Pete is in the second year of lower secondary while Molly is in the third (final) year. Molly's exposure to the SCM programme will be eight months while Pete's exposure will be 18 months at the time of the final examination in 2017 and 2018, respectively.[7] This plausibly exogenous variation in the intensity of exposure within the same student cohort is derived from the staggered roll-out of the programme. It is also important to note that the within-school variations in the programme exposure are also associated with variations in students' grades (age). Also, as different local municipalities (districts) introduced the programme in different months, there is a variation in months rather than years of exposure across municipalities, schools, and student cohorts. In general, the cumulative exposure of students to the SCM programme is between 0 and 30 'school' months.

To estimate the causal impact of the programme exposure, we begin with the following baseline model which exploits the variation in months of the programme induced by the staggered implementation across schools and student grade (age) at the time of implementation:

$$y_{ist} = \alpha_s + \lambda_t + YOB_{FE} + \omega SCM_{ist} + \gamma X_{ist} + _{ist} \tag{1}$$

[5] However, due to grade repetition, dropout, and re-entry into the school system, not all students in the same grade are of the same age. Interestingly, the average age of both female and male students at the time of the O-level exam seems to be higher than expected. For instance, Figure 4 shows that a high percentage of Rwandan lower secondary school students sit for national exams at 17 years old. We control for this by absorbing student birth-year fixed effects.

[6] For identification purposes, we also consider the school year for each cohort over the years under study.

[7] In Rwanda, after a student completes grade 6 of primary school, they join junior high school (locally know as tronc commun / ordinary or simply lower secondary schools). This cycle lasts three years, after which all students sit a national exam that is used for progressive metrics at upper secondary schools.

The y_{ist} is the outcome variable, the standardized grades of student i in school s, sitting a national exam at year t; α_s and λ_t representing the school and exam year fixed effects, respectively; SCM_{ist} is the cumulative number of school months a student i who studied in school s and took the national exam in year t was exposed to the SCM programme. The ω is our parameter of interest. We also accounted for student's gender, as provided by the X_{ist}. In this model, various fixed effects have been accounted for. The inclusion of school fixed effects α_s absorbs time-invariant differences across schools, while the exam year fixed effects, λ_t accounts for contemporaneous shocks that affects all schools in a given year. In different specifications, we replace the exam-year fixed effect with the district-exam-year fixed effects to absorb district-specific contemporaneous shocks. Finally, to account for the unobserved factors for the student performance and grade progression across age cohorts, we include birth year fixed effect, YOB_{FE}. The latter allows us to deal with issues of repetition rates, for example, and its potential implications on students' performance. Finally, the error term, $_{ist}$ is included in our model to correlate between students in the same schools but independent in different schools.

3.2 Data sources and descriptives

To conduct this study, we use administrative data on students' scores on five STEM subjects—mathematics, physics, biology, chemistry, and geography—in lower secondary school national examinations in Rwanda. The scores come from the National Examination and School Inspection Authority (NESA), a public institution with a mandate of administrating comprehensive assessments for basic education in the country. The scores are measured by grade points that range from 1 to 10, 10 being the highest. All grade points have been standardized for each year and subject. The dataset also contains the age and gender of each student, and the unique school ID for the period between 2015 and 2021. A second dataset contains the schools under the SCM programme and their dates of enrollment into the programme received from the Rwanda Basic Education Board (REB). We finally use a third dataset on teacher placement and school leadership from REB to examine the potential mechanisms. The teacher placement data contains the yearly information of each school's employees (teachers and supporting staff), including their gender. In addition, the dataset provides information on the school leadership: school manager and deputies in charge of studies and in charge of school discipline for four academic years, 2016–19. Our final dataset includes 318,643 students from 772 schools considered under the SCM programme across 30 districts. Figure 5 shows the geographic distribution of SCM school beneficiaries across the 30 districts in Rwanda.

Table 1 shows the summary statistics of the main variables used in this study. The table indicates that the majority (55 per cent) of exam candidates are females. It also shows that the average age of students at the time of the exam is 17 years, and only 19 per cent of all schools are boarding schools. The mean value of student exposure to the SCM programme is 8.99

(school) months, and the highest is 30 (school) months of exposure to the programme. On average, 46 per cent of 635 schools are led by female school managers, while 14 per cent of the deputies in charge of studies are females.[8]

4 Results and discussions

4.1 Event in rolling out the SCM programme

There are two main assumptions for the causal interpretation of ω from our baseline model, as suggested by Callaway and Sant'Anna (2021) and Borusyak et al. (2024). The first assumption is that the roll-out of the programme is uncorrelated with underlying trends at the schools. In other words, we need the students' grade points between 'early' and 'late' beneficiary schools to follow parallel trends in the absence of the SCM programme. In this respect, we show evidence of this assumption by indicating that pre-event trends are essentially similar for the student grades for early adopters and late adopters. Also, by relying on the timing that the school becomes a SCM beneficiary (event incidence) together with the exogenous variation in the exposure student (age) cohort, we can be more confident that we are comparing students with the same trends. The second assumption is that we need the schools (hence the students) not to anticipate the SCM programme, implying that there should not be an impact of the SCM programme in the future on the current outcomes (Abbring and Van den Berg 2003). Although this 'no-anticipation' is sometimes difficult to hold, it is fair to say that in this context, the schools cannot decide when to receive SCM as this is mainly a national programme, whose roll-out is decided at the ministry level. For this reason, we can assume that the second assumption holds.

To address the concern in the first assumption, we conduct an event study to derive the trends in students' performance before and after the start of the programme in various schools based on the following equation:

$$y_{ist} = \alpha_s + \lambda_t + YOB_{FE} + \sum_{\varkappa=-3}^{3} \psi_\varkappa \times \mathbb{1}(t = t_{st}^{SCM} + \varkappa) + \gamma X_{ist} + {}_{ist} \tag{2}$$

where $\varkappa$ represents the number of years relative to the year in which SCM was introduced into the school. Following Borusyak et al. (2024), we omit time periods zero (0) since all schools in our sample are eventually treated at this period. Using Equation 2, we estimate the event study as shown in Figure 9. From the estimates, we show that the average differences in test grades between early and late beneficiary schools before the programme are statistically indif-

[8] In a period of five years (2017–21), Rwanda has established smart classrooms in 772 (O-level) secondary schools. However, the teacher placement data goes up to 2019 and only captures 82.25 per cent of the SCM beneficiary schools.

ferent. The figure, however, indicates statistical differences (increases) in student test grades in some STEM grades in the years following the roll-out of the SCM programme, at least in the third year between early and late beneficiary schools. This suggests that 'early' and 'late' school beneficiaries were comparable and hence, the timing of the SCM programme roll-out was not driven by factors that are systematically correlated with student performance. Also, it is important to mention that the increase in student performance over time suggests that the treatment effects estimated hereafter are not driven by some (random) local shocks other than the effects induced by the SCM programme. Therefore, conditional on our identifying assumptions, $\hat{\omega}$ from Equation (1) measures the effect of exposure to the SCM programme on school performance. We also considered the likely biased estimates due to the presence of negative weighting in conventional two-way fixed effect estimator (TWFE) models with staggered treatment (Callaway and Sant'Anna 2021; Goodman-Bacon 2021; Baker et al. 2022). In this respect, we estimate an alternative event study based on the recent method by Callaway and Sant'Anna (2021) to derive a robust analysis with multiple periods and variations in treatment timing. The results are shared in Figures 12–14. Three years after the school got a smart classroom, we do not find any statistical differences in students' performance between those who sat the national exam before and after the SCM, albeit some indication of an upward trend in performance in some subjects such as geography, physics, mathematics, and aggregate scores, at least in the third year of the SCM programme. In general, the findings from Callaway and Sant'Anna (2021) reaffirm the earlier results of the relatively small effect of exposure to SCM on student test scores and support the robustness of our baseline model to the plausible biases resulting from the staggered implementation of the SCM across schools.

4.2 Smart classrooms and learning outcomes

The results in Table 2 indicate that the exposure to SCM produced overall positive albeit small impacts on test grade points, increasing the aggregate grade by about 0.0024 standard deviation for every month of the programme's exposure. The positive results are driven by specific subjects, namely physics, biology, and geography, with the impact sizes being between 0.002 and 0.004 standard deviation increase in test grade points and nil effect for mathematics and chemistry. This is consistent with previous findings on the heterogeneous effects of similar programmes on different subjects. For example, Fernández-Gutiérrez et al. (2020) reckon that other science subjects may benefit more from use of ICT than mathematics, especially in cases where students are in a self-guided information-finding mission. Some subject teachers or subjects such as mathematics may also require more support and guidance on how to integrate ICT in teaching (Nelson et al. 2019). As a result, the SCM programme may therefore have quicker and positive results on some subjects than in others, especially in cases where the students may be required to do self-guided learning.

We also investigate whether the impact of the treatment varies with the intensity of the exposure that varies with the number of months of exposure. Figure 10 shows that the impact of the programme increases with the increase in the number of months of exposure. While the impact is almost nil in the first ten months of exposure, especially for maths, biology, and physics, the effect sizes are positive and increasing after 11 months of exposure. After 21 months, the impact of the SCM programme is positive for all subjects. These results are consistent with the findings in Bando et al. (2017), who find nil effect of a programme that introduced digital learning by replacing paper books with computers after one year of the programme. The use of computers for learning requires an adjustment period for both teachers and students, and therefore the impact may be realised with a lag. We also note that in the case of the SCM programme in Rwanda, teacher training was not tailored to the different subjects. and this may explain the slow adaptation as well as the small effect sizes. For effective utilization of the ICT in specific subjects, tailored training to each subject may be required. Our results (Figure11) also indicate that students who get early exposure (at a younger age) benefit more from the programme, with the positive SCM programme effects being highest for the students who get the exposure at age 11 and declining with the increase of the earliest age at exposure[9].

5 Heterogeneous treatment effects of the SCM programme

5.1 SCM programme and gender gaps

This section provides the degree to which the SCM programme can bridge the gender gaps in academic performance in science subjects in secondary education. Equality among female and male students is not only a fundamental human right but also a key factor for a prosperous and global modern economy that allows sustainable, inclusive growth (OECD 2018). To explore the effect of SCM on gender gaps in academic outcomes, we interact our exposure variable with the female student dummy variable and estimate a variant model in Equation (3):

$$y_{ist} = \alpha_s + \lambda_t + YOB_{FE} + \omega_1 SCM_{ist} + \omega_2 SCM_{ist} \times Female + \beta Female_{ist} + _{ist} \quad (3)$$

where all variables remain as previously defined. From this expression, the parameter ω_1 estimates the effect of SCM on male students' test grade points, while ω_2 measures the relative contribution of exposure to the SCM programme on the girls' performance relative to male students. Based on Equation (3), we can identify the total effects of the programme on female students as provided by $\omega_1 + \omega_2$. Further, the β estimate measures the gender gap in student performance if the effect of the SCM is gender neutral (meaning that ω_2=0). Therefore, the overall gender difference in student performance is provided by $\hat{\beta} + \hat{\omega_2} \times \overline{SCM}$, which

[9] It is important to note that the earliest age at exposure, and the age of starting low secondary school, is 11 year old as per education law).

consists of the gender gap in learning outcomes in the absence of the programme, $\hat{\beta}$, and the programme-induced gender gap, $\hat{\omega_2} \times \overline{SCM}$, evaluated at the average level of exposure. The relative contribution of the programme on gender gaps in student performance is hence given as $\left(\hat{\omega_2}/\hat{\beta}\right) \times \overline{SCM}$. Based on this expression, we can say that the programme reduces (increases) gender inequality when the ratio is negative (positive).

The findings on the SCM programme and the gender gap are reported in Table 3. The table contains two sections (Panel A & B). In Panel A, we measure the gender gap by interacting the continuous measure of exposure (in months) with the dummy for female students. On the other hand, in Panel B, we measure the gaps between female and male students by interacting the female student dummy with dummy variables for varying years of exposure to the SCM programme. Specifically, from Panel A, the study shows that introducing SCM positively improves test scores for both boys and girls, although the effect is small in magnitude.[10] The study shows that a one-month exposure to the SCM induces an increase in boys' performance in physics, geography, and aggregate scores by 0.0023, 0.0020, and 0.0016 standard deviations, respectively. On the other hand, the corresponding changes for girls' test scores in physics, geography, and aggregate scores are given by 0.0035, 0.0052, and 0.0032 standard deviations, respectively.[11] For the other subjects (biology, chemistry), the findings show that a one-month SCM exposure leads to an increase in girls' performance between 0.0012 and 0.0017 sigma relative to boys. In brief, we can say that with different specifications, and across the two panels, the parameter estimates of the interaction term are positive and statistically significant, albeit small in magnitude, except in mathematics, hence suggestive evidence that the SCM programme improves the learning outcomes for female students relative to their male counterparts.[12]

5.2 SCM programme and school types

To estimate heterogeneous effects across different school types, we estimate the impact of the programme on public schools and a 'nine-twelve-years' school sub-sample, and also interact the treatment with different school types, namely government-aided and boarding schools. The impact in public schools in Table 5 is nil for the aggregate scores and all specific subjects except geography. The government subsidizes education in all public schools, and parents are not required to contribute to the school fees. The schools do not get support from the private sector either, such as religious institutions. This creates the differences between public schools and the government-aided schools. When we interact the treatment with the government-aided schools in Table 7, we find a treatment effect of about 0.007 standard deviation on the aggregate scores

[10] In all specifications, the effects of the SCM on girls' performance is higher relative to boys.

[11] Total effects of the SCM programme on girls' test scores are given by: 0.0035(0.0023+0.0012); 0.0052(0.0020+0.0032); and 0.0032(0.0016+0.0016).

[12] In this study, the results have shown that the SCM programme does not have any effect on mathematics test grades, and the results remain unchanged in all specifications.

and a positive effect on all the subjects except biology and geography. The results here underpin the importance of public–private partnerships in education and support other evidence, such as Romero et al. (2020) and Barrera-Osorio et al. (2022) who find that such partnerships improve efficiency in delivering education, eventually improving learning outcomes.

The treatment effect is also nil for the 'nine-twelve-years' school sub-sample except for geography, see Table 8. 'Nine-twelve-years' schools in Rwanda are all-day schools that offer grades 1–12 education. We compare these results with the ones from boarding schools. We find a larger effect size on the interaction of the treatment and boarding school, as reported in Table 6, with an increase of about 0.01 standard deviation on the aggregate grade and in all subjects for each month of exposure to the SCM programme. It may be argued that since students are selected into boarding schools based on their performance in the national exam at the grade 6 level, the effect could be arising from self-selection. However, we control for this using school fixed effects. It may also be possible that boarding school learners get more time for self-study in the computer classes due to time spent in school, compared to day-school students who have limited school hours. We however do not have data on time spent in computer classes outside normal school hours.

5.3 SCM programme and age at exposure

The use of ICT and smart classrooms can enhance and speed up the student learning process when it is well integrated with traditional teaching-learning methods. The extant literature has also shown that the learners' familiarity with class technologies and their early-life exposure to technology helped to explain math and science achievement gaps between students and schools (Li and Atkins 2004; Delen and Bulut 2011). This explains that early-life exposure to smart classrooms is associated with students' school readiness and cognitive development. Hence, in this study, we expect that SCM will be more beneficial for the students who were exposed to the programme at an early age compared to older cohorts. In this section, we examine the heterogeneity in the effect of the SCM according to student age at first exposure to the SCM programme by deriving the following expression:

$$y_{ist} = \alpha_s + \lambda_t + cohort_{FE} + \sum_{\varkappa=11}^{17} \psi_\varkappa \times (SCM_{ist} \times T_{ik}) + \gamma X_{ist} + {}_{ist} \tag{4}$$

where T_{ik} is an indicator variable that shows if the student i is of age k in the year the SCM was introduced into their school. The control category is the group of students aged 18–21 at the time of first exposure to the SCM programme. The $cohort_{FE}$ accounts for the cohort fixed effects.[13] The results from Equation 4 are reported in Figure 11, where we plot the coefficients,

[13] The students aged between 11 and 16 and those aged 17–21 in the year when the SCM programme was launched in their respective schools.

$\psi_{\varkappa}$, of the interaction between cumulative months of exposure to the SCM programme and the indicator for a given student being in a particular age group at the time of first exposure to the SCM programme. The parameter estimates represent the effect of the within-school variations in the programme intensity on a given cohort. Taking students who get their first exposure to the SCM programme at age 11 as an example, their test grade points in mathematics, physics, and STEM aggregate increased by 0.024(0.020)0.021 for each additional month of the exposure to the SCM programme, respectively. In conclusion, the effect of the SCM programme on STEM academic achievements is high when students are exposed to the programme at an early age, and this is likely associated with the speed of development of the cognitive ability of the learners at a young age.

6 Mechanisms

So far, our results have shown overall positive effects of exposure to SCM on student performance in STEM subjects. This section explores two potential channels through which technological exposure may induce student performance. To this end, we use two datasets from the Rwanda Basic Education Board on school teachers and leadership placements and the total number of computers per school. In the first dataset on school teachers and leadership placements, we can identify the gender of the school manager (SM) and deputy school manager in charge of studies (DoS) for every school year. The main limitation of the dataset is that while we can observe every teacher and their core teaching subjects, we are not able to know whether the teacher was responsible for teaching STEM subjects. Nevertheless, we use the gender of the SM and DoS in the reduced form to examine whether female school managers can induce the use of SCM in student performance. The second dataset is the distribution of school computers in secondary schools in the country. We use this to compute the student-computer ratio for every school year. We therefore examine the effects of the gender of SM, DoS, and intensity of computer availability on student test grades. The results provide us with some suggestive evidence of how school leadership and infrastructure can be helpful in explaining our baseline results.

6.1 SCM and student test scores: the role of gender in school leadership

Other channels through which the SCM can affect the students' test scores include the gender of school leadership. We explore whether there is a statistical difference between schools led by female school managers relative to those governed by male counterparts. To explore this, we interact our exposure variable with the dummy variable for female school managers (SM) and deputy school managers in charge of studies (DoS) and estimate a variant reduced-form model as provided by the following expressions 5 and 6:

$$y_{ist} = \alpha_s + \lambda_t + YOB_{FE} + \omega_1 SCM_{ist} + \omega_2 SCM_{st} \times FemaleSM + \beta FemaleSM_{st} + _{ist} \tag{5}$$

$$y_{ist} = \alpha_s + \lambda_t + YOB_{FE} + \omega_1 SCM_{ist} + \omega_2 SCM_{st} \times FemaleDoS + \beta FemaleDoS_{st} + {}_{ist} \quad (6)$$

where $FemaleSM_{st}$ is an indicator variable showing if the manager of the school s is a female at a given school year t, while $FemaleDoS_{st}$ is an indicator variable showing if the deputy school manager in charge of studies (DoS) in school s is a female during school year t. Through different specifications, Table 11 shows that there are no statistical differences in student test scores results when schools are managed by females or male. Alternatively, we can say that the effect of SCM exposure on students' test scores is not driven by the gender of the school manager. We also explore whether the gender of the deputy school manager in charge of studies (DoS) can matter for the students' performance when exposed to SCM. To do this, we estimate the reduced-form model, including the gender of DoS and its interaction with the variable of interest (exposure), and the results are reported in Table 12 with two main findings. First the schools that have the female DoS are likely to perform relatively less compared to those led by male counterparts, as indicated in the first row of Table 12. Second, the study shows that schools that have female DoS and benefit from the SCM programme are more likely to perform better in the national exam compared to those managed by male counterparts.

6.2 Degree of computer access: student-computer ratio

Our first mechanism through which the SCM can induce the impact on student test scores is through access to enough and reliable computers. To do this, we approximate the student-computer ratio in each school using lower secondary school students who sat for a national exam every year relative to the number of available computers at the school. Ideally, the student-computer ratio shows the distribution of SCM resources across districts as indicated by Figure 8. As shown in the same figure, some districts have more than a 1-1 ratio. Looking at the potential effect of the student-computer ratio on the test scores, the findings show a negative correlation between the student-computer ratio and test scores in all subjects. Interestingly, the study shows that student performance is driven by the ratio of a computer to students, hence the intensity of the SCM exposure, as indicated by the interaction term of Table 10.

7 Conclusion and Implications

In 2016, the Rwanda government launched a smart classroom programme under which more than 772 middle schools benefited from a SCM programme between 2017 and 2021. The programme intends to integrate the technology in the traditional teaching-learning system, where classroom technology packages (computers and internet access) are provided in specific rooms—'smart classrooms'—and students are more often required to use the smart classrooms as part of teaching-learning process. While the focus of this study has been on the learning effect of the SCM programme, it is important to remember that this is, if anything, an additional benefit of the programme. The overall goal of the SCM policy was to allow middle-school-aged students to acquire relevant skills in digital literacy, and available evidence suggests a strong linkage between digital skills, labour market, and employment opportunities. For instance, in a careful analysis, Snape (2017) shows that digital literacy is one of the most desirable 'soft skills' for the new career and workplace opportunities in the current global economies. In this study, we leverage the staggered implementation of the SCM programme across schools and plausibly exogenous variations in the exposure across student cohorts to examine the impact of the SCM programme on students' test scores in Rwanda.

The study findings show heterogeneous effects of the programme on learning outcomes in STEM subjects. We find a statistically significant effect of the SCM programme on student scores in physics, biology, and geography, while no effects were detected in test scores in mathematics and chemistry. Further, we show that smart classrooms are more beneficial for students who are exposed at a relatively early age. In addition, the findings provide suggestive evidence that such programmes can actually be a channel to reducing the existing gender gaps in learning. Although the programme seems to have induced benefits to both male and female students, the suggested evidence indicates that female students benefited more from the SCM programme relative to their male counterparts. Finally, the study finds that the effect is more pronounced among government-aided schools, suggesting the role of public–private partnership in human capital development.

References

Abbring, J. H., and Van den Berg, G. J. (2003). 'The Nonparametric Identification of Treatment Effects in Duration Models'. *Econometrica*, 71(5): 1491–517. https://doi.org/10.1111/1468-0262.00456

Bai, Y., Tang, B., Wang, B., Mo, D., Zhang, L., Rozelle, S., Auden, E., and Mandell, B. (2023). 'Impact of Online Computer Assisted Learning on Education: Experimental Evidence from Economically Vulnerable Areas of China'. *Economics of Education Review*, 94(June): 102385. https://doi.org/10.1016/j.econedurev.2023.102385

Baker, A. C., Larcker, D. F., and Wang, C. C. (2022). 'How much Should We Trust Staggered Difference-in-differences Estimates?' *Journal of Financial Economics*, 144(2): 370–95. https://doi.org/10.1016/j.jfineco.2022.01.004

Bando, R., Gallego, F., Gertler, P., and Fonseca, D. R. (2017). 'Books or Laptops? The Effect of Shifting from Printed to Digital Delivery of Educational Content on Learning'. *Economics of Education Review*, 61(December): 162–73. https://doi.org/10.1016/j.econedurev.2017.07.005

Barrera-Osorio, F., Blakeslee, D. S., Hoover, M., Linden, L., Raju, D., and Ryan, S. P. (2022). 'Delivering Education to the Underserved through a Public-Private Partnership Program in Pakistan'. *Review of Economics and Statistics*, 104(3): 399–416. https://doi.org/10.1162/rest_a_01002

Bold, T., Kimenyi, M., Mwabu, G., Ng'ang'a, A., and Sandefur, J. (2018). 'Experimental Evidence on Scaling up Education Reforms in Kenya'. *Journal of Public Economics*, 168(December): 1–20. https://doi.org/10.1016/j.jpubeco.2018.08.007

Borusyak, K., Jaravel, X., and Spiess, J. (2024). ‘Revisiting Event Study Designs: Robust and Efficient Estimation’. *Review of Economic Studies*, corrected proof(-): rdae007. https://doi.org/10.1093/restud/rdae007

Bowman, M. A., Vongkulluksn, V. W., Jiang, Z., and Xie, K. (2022). ‘Teachers’ Exposure to Professional Development and the Quality of their Instructional Technology use: The Mediating Role of Teachers’ Value And Ability Beliefs’. *Journal of Research on Technology in Education*, 54(2): 188–204. https://doi.org/10.1080/15391523.2020.1830895

Callaway, B., and Sant’Anna, P. H. (2021). ‘Difference-in-differences with Multiple Time Periods’. *Journal of Econometrics*, 225(2): 200–30. https://doi.org/10.1016/j.jeconom.2020.12.001

Cardim, J., Molina-Millán, T., and Vicente, P. C. (2023). ‘Can Technology Improve the Classroom Experience in Primary Education? An African Experiment on a Worldwide Program’. *Journal of Development Economics*, 164(September): 103145. https://doi.org/10.1016/j.jdeveco.2023.103145

Chakraborty, T., and Jayaraman, R. (2019). ‘School Feeding and Learning Achievement: Evidence from India’s Midday Meal Program’. *Journal of Development Economics*, 139(June): 249–65. https://doi.org/10.1016/j.jdeveco.2018.10.011

Chen, C.-H., and Tsai, C.-C. (2021). ‘In-service Teachers’ Conceptions of Mobile Technology-integrated Instruction: Tendency towards Student-centered Learning’. *Computers & Education*, 170(September): 104224. https://doi.org/10.1016/j.compedu.2021.104224

Delen, E., and Bulut, O. (2011). ‘The Relationship between Students’ Exposure to Technology and their Achievement in Science and Math’. *Turkish Online Journal of Educational Technology-TOJET*, 10(3): 311–17.

Derksen, L., Michaud-Leclerc, C., and Souza, P. C. (2022). ‘Restricted Access: How the Internet Can Be Used to Promote Reading and Learning’. *Journal of Development Economics*, 155(March): 102810. https://doi.org/10.1016/j.jdeveco.2021.102810

Drexler, A., Fischer, G., and Schoar, A. (2014). ‘Keeping it Simple: Financial Literacy and Rules of Thumb’. *American Economic Journal: Applied Economics*, 6(2): 1–31. https://doi.org/10.1257/app.6.2.1

Duflo, E., Dupas, P., and Kremer, M. (2011). ‘Peer Effects, Teacher Incentives, and the Impact of Tracking: Evidence from a Randomized Evaluation in Kenya’. *American Economic Review*, 101(5): 1739–774. https://doi.org/10.1257/aer.101.5.1739

Fernández-Gutiérrez, M., Gimenez, G., and Calero, J. (2020). ‘Is the Use of ICT in Education Leading to Higher Student Outcomes? Analysis from the Spanish Autonomous Communities’. *Computers & Education*, 157(November): 103969. https://doi.org/10.1016/j.compedu.2020.103969

Filmer, D., Langthaler, M., Stehrer, R., and Vogel, T. (2018). *World Development Report 2018: Learning to Realize Education’s Promise.* Washington, DC: Wold Bank Group.

Ghavifekr, S., and Rosdy, W. A. W. (2015). ‘Teaching and Learning with Technology: Effectiveness of ICT Integration in Schools’. *International Journal of Research in Education and Science*, 1(2): 175–91.

Goodman-Bacon, A. (2021). ‘Difference-in-differences with Variation in Treatment Timing’. *Journal of Econometrics*, 225(2): 254–77. https://doi.org/10.1016/j.jeconom.2021.03.014

Grek, S., and Landri, P. (2021). 'Editorial: Education in Europe and the COVID-19 Pandemic'. *European Educational Research Journal*, 20(4): 393–402. https://doi.org/10.1177/14749041211024781

Gust, S., Hanushek, E. A., and Woessmann, L. (2023). 'Global Universal Basic Skills: Current Deficits and Implications for World Development'. *Journal of Development Economics*, 166(January): 103205. https://doi.org/10.1016/j.jdeveco.2023.103205

Hanushek, E. A. (2003). 'The Failure of Input-based Schooling Policies'. *The Economic Journal*, 113(485): F64–98. https://doi.org/10.1111/1468-0297.00099

Jones, S., Schipper, Y., Ruto, S., and Rajani, R. (2014). 'Can your Child Read and Count? Measuring Learning Outcomes in East Africa'. *Journal of African Economies*, 23(5): 643–72. https://doi.org/10.1093/jae/eju009

Karabenick, S. A. (2011). 'Classroom and Technology-supported Help Seeking: The Need for Converging Research Paradigms'. *Learning and Instruction*, 21(2): 290–96. https://doi.org/10.1016/j.learninstruc.2010.07.007

König, J., Jäger-Biela, D. J., and Glutsch, N. (2020). 'Adapting to Online Teaching during COVID-19 School Closure: Teacher Education and Teacher Competence Effects among Early Career Teachers in Germany'. *European Journal of Teacher Education*, 43(4): 608–22. https://doi.org/10.1080/02619768.2020.1809650

Lawrence, J. E., and Tar, U. A. (2018). 'Factors that Influence Teachers' Adoption and Integration of ICT in Teaching/Learning Process'. *Educational Media International*, 55(1): 79–105. https://doi.org/10.1080/09523987.2018.1439712

Li, X., and Atkins, M. S. (2004). 'Early Childhood Computer Experience and Cognitive and Motor Development'. *Pediatrics*, 113(6): 1715–22. https://doi.org/10.1542/peds.113.6.1715

MINEDUC (2016). *ICT in Education Policy.* Kigali: Ministry of Education, Republic of Rwanda.

MINEDUC (2017). *Education Sector Strategic Plan 2018/19 to 2023/24.* Kigali: Ministry of Education, Republic of Rwanda.

Muralidharan, K., Singh, A., and Ganimian, A. J. (2019). 'Disrupting Education? Experimental Evidence on Technology-aided Instruction in India'. *American Economic Review*, 109(4): 1426–60. https://doi.org/10.1257/aer.20171112

Nelson, M. J., Voithofer, R., and Cheng, S.-L. (2019). 'Mediating Factors that Influence the Technology Integration Practices of Teacher Educators'. *Computers & Education*, 128(January): 330–44. https://doi.org/10.1016/j.compedu.2018.09.023

OECD (2018). *Bridging the Digital Gender Divide: Include, Upskill, Innovate.* Paris: OECD.

Primature (2017). *7 Years Government Programme: National Strategy for Transformation (NST1), 2017–2024.* Kigali: Office of the Prime Minister.

REB (2018). *Smart Classroom Design. Concept Note.* Kigali: Rwandan Basic Education Board. (September 2018)

Romero, M., Sandefur, J., and Sandholtz, W. A. (2020). 'Outsourcing Education: Experimental Evidence from Liberia'. *American Economic Review*, 110(2): 364–400. https://doi.org/10.1257/aer.20181478

Rouse, C. E., and Krueger, A. B. (2004). 'Putting Computerized Instruction to the Test: A Randomized

Evaluation of a “Scientifically Based” Reading Program’. *Economics of Education Review*, 23(4): 323–38. https://doi.org/10.1016/j.econedurev.2003.10.005

Sangrà, A., and González-Sanmamed, M. (2010). ‘The Role of Information and Communication Technologies in Improving Teaching and Learning Processes in Primary and Secondary Schools’. *ALT-J*, 18(3): 207–20. https://doi.org/10.1080/09687769.2010.529108

Snape, P. (2017). ‘Enduring Learning: Integrating C21st Soft Skills through Technology Education’. *Design and Technology Education*, 22(3): n3.

Valente, C. (2019). ‘Primary Education Expansion and Quality of Schooling’. *Economics of Education Review*, 73(December): 101913. https://doi.org/10.1016/j.econedurev.2019.101913

Vivalt, E. (2020). ‘How much Can We Generalize from Impact Evaluations?’ *Journal of the European Economic Association*, 18(6): 3045–89. https://doi.org/10.1093/jeea/jvaa019

Yildirim, S. (2007). ‘Current Utilization of ICT in Turkish Basic Education Schools: A Review of Teacher’s ICT Use and Barriers to Integration’. *International Journal of Instructional Media*, 34(2): 171.

Tables

Main results

Table 1: Descriptive and summary statistics

Variable	Mean	Std. dev.	Min.	Max.	N
Student age at exam time	17.11	1.59	14	21	318643
Female students	0.55	0.49	0	1	324822
Rural schools	0.78	0.41	0	1	324822
boarding_school	0.19	0.39	0	1	324822
Private schools	0.04	0.19	0	1	324822
Government-aided schools	0.58	0.49	0	1	324822
Public schools	0.38	0.48	0	1	324822
Twelve years basic schools	0.81	0.38	0	1	324822
Combined lower & upper high schools	0.18	0.38	0	1	324822
Vocational schools	0.01	0.07	0	1	324822
Female school managers (SM)	0.46	0.49	0	1	244412
Female Deputy of Studies(DoS)	0.14	0.34	0	1	244412
months exposed to smart-class	8.99	11.17	0	30	324822
No-exposure	0.53	0.49	0	1	324822
Exposed 1–10 months	0.17	0.37	0	1	324822
Exposed 11–20 months	0.15	0.36	0	1	324822
Exposed 21–30 months	0.14	0.35	0	1	324822
Standardized values of grade_math_rev	0	1	-1.18	2.99	324822
Standardized values of grade_phys_rev	0	1	-1.05	3.45	324822
Standardized values of grade_biolo_rev	0	1	-1.16	3.10	324822
Standardized values of grade_chemi_rev	0	1	-0.79	4.01	324822
Standardized values of grade_geo_rev	0	1	-1.03	2.97	324822
Standardized values of total_grade_rev	0	1	-1.10	3.32	324822

Table 2: Effect of smart classrooms on student performance (baseline)

	Mathematics				Physics			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Exposure (months)	0.0012	0.0014	0.0012	0.0013	0.0029***	0.0030***	0.0029***	0.0029***
	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0011)	(0.0011)	(0.0011)	(0.0011)
Female	-0.1331***	-0.1331***	-0.1852***	-0.1853***	-0.2974***	-0.2974***	-0.3482***	-0.3483***
	(0.0051)	(0.0051)	(0.0051)	(0.0057)	(0.0057)	(0.0058)	(0.0058)	
R-squared	0.3444	0.3466	0.3766	0.3788	0.4422	0.4444	0.4729	0.4751
	Biology				Chemistry			
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Exposure (months)	0.0024**	0.0022**	0.0024**	0.0021**	0.0014	0.0015	0.0014	0.0014
	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0011)	(0.0011)	(0.0011)	(0.0011)
Female	-0.3473***	-0.3471***	-0.3969***	-0.3968***	-0.2685***	-0.2684***	-0.3125***	-0.3124***
	(0.0060)	(0.0060)	(0.0061)	(0.0061)	(0.0057)	(0.0057)	(0.0061)	(0.0061)
R-squared	0.4259	0.4281	0.4547	0.4568	0.4203	0.4224	0.4436	0.4457
	Geography				Aggregate scores			
	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)
Exposure (months)	0.0034***	0.0037***	0.0034***	0.0037***	0.0024***	0.0025***	0.0024***	0.0024***
	(0.0009)	(0.0009)	(0.0009)	(0.0010)	(0.0009)	(0.0009)	(0.0009)	(0.0009)
Female	-0.4632***	-0.4631***	-0.5099***	-0.5098***	-0.3351***	-0.3350***	-0.3897***	-0.3896***
	(0.0064)	(0.0064)	(0.0066)	(0.0066)	(0.0058)	(0.0058)	(0.0059)	(0.0059)
R-squared	0.4563	0.4584	0.4816	0.4838	0.4906	0.4921	0.5256	0.5271
School FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Exam year FE	Yes	No	Yes	No	Yes	No	Yes	No
YOB FE	No	No	Yes	Yes	No	No	Yes	Yes
District $\times$ Year FE	No	Yes	No	Yes	No	Yes	No	Yes
Observations	324822	324822	324821	324821	324822	324822	324821	324821

Note: dependent variables are the standardized grade points of the five science subjects done in the lower secondary school final national exam and the aggregate grade. The grades are standardized for each exam year. The exposure stands for the number of months each student was exposed to the smart classroom programme prior to sitting the national exam. Standard errors are clustered at school level and reported in parentheses. * significant at 10 per cent level; ** significant at 5 per cent level; *** significant at 1 per cent level.

Table 3: Smart classrooms and gender gaps in education

	Maths	Physics	Biology	Chemistry	Geography	Aggregate scores
				Panel A		
	(1)	(2)	(3)	(4)	(5)	(6)
Female	-0.1809***	-0.3594***	-0.4096***	-0.3275***	-0.5383***	-0.4040***
	(0.0060)	(0.0064)	(0.0071)	(0.0067)	(0.0072)	(0.0065)
Exposure (months)	0.0016	0.0023**	0.0013	0.0005	0.0020**	0.0016*
	(0.0010)	(0.0011)	(0.0009)	(0.0011)	(0.0010)	(0.0009)
× Female	-0.0005	0.0012***	0.0014***	0.0017***	0.0032***	0.0016***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Coef. on Exposure + Exposure× Female=0						
F-stat	1.1500	0.2200	10.5300	7.6200	8.1200	4.2800
p-value	0.2838	0.6387	0.0012	0.0059	0.0044	0.0389
Change % in gender gap						
R-squared	0.3788	0.4751	0.4569	0.4458	0.4841	0.5272
				Panel B		
Female	-0.1800***	-0.3614***	-0.4048***	-0.3296***	-0.5377***	-0.4037***
	(0.0063)	(0.0067)	(0.0073)	(0.0071)	(0.0076)	(0.0068)
exposure_1_10	0.0004	0.0020	0.0260	0.0220	0.0285	0.0146
	(0.0190)	(0.0190)	(0.0183)	(0.0199)	(0.0184)	(0.0165)
× Female	-0.0072	0.0299***	-0.0372***	0.0193*	0.0236**	0.0079
	(0.0108)	(0.0107)	(0.0112)	(0.0110)	(0.0113)	(0.0102)
exposure_11_20	0.0273	0.0383	0.0028	-0.0114	0.0301	0.0190
	(0.0242)	(0.0260)	(0.0227)	(0.0274)	(0.0239)	(0.0215)
× Female	-0.0197*	0.0074	0.0656***	0.0559***	0.0623***	0.0384***
	(0.0112)	(0.0109)	(0.0122)	(0.0130)	(0.0118)	(0.0110)
exposure_21_30	0.0369	0.0652*	0.0412	0.0370	0.0647**	0.0494*
	(0.0308)	(0.0332)	(0.0299)	(0.0360)	(0.0313)	(0.0277)
× Female	-0.0072	0.0468***	0.0280**	0.0352***	0.0967***	0.0461***
	(0.0122)	(0.0130)	(0.0119)	(0.0123)	(0.0130)	(0.0117)
R-squared	0.3788	0.4752	0.4571	0.4458	0.4840	0.5274
School FE	Yes	Yes	Yes	Yes	Yes	Yes
District-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
YOB FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	324821	324821	324821	324821	324821	324821

Note: dependent variables are the standardized grade points of the five science subjects done in the lower secondary school final national exam and the aggregate grade. The grades are standardized for each exam year. The exposure stands for the number of months each student was exposed to the smart classroom programme prior to sitting the national exam. Standard errors are clustered at school level and reported in parentheses. * significant at 10 per cent level; ** significant at 5 per cent level; *** significant at 1 per cent level.

Table 4: Exam timetable for the ordinary level (lower secondary) school students

Mathematics		Kinyarwanda		History		Geography		Physics	
Date	Time	Date	Time	Date	Time	Date	Time	Date	Time
2021-07-26	8:30-11:30	2021-07-26	14:00-17:00	2021-07-27	8:30-11:30	2021-08-01	8:30-11:30	2021-07-28	8:30-11:30
2019-11-12	8:30-11:30	2019-11-12	14:00-17:00	2019-11-13	8:30-11:30	2019-11-18	8:30-11:30	2019-11-14	8:30-11:30
2018-11-20	8:30-11:30	2018-11-20	14:00-17:00	2018-11-21	8:30-11:30	2018-11-26	8:30-11:30	2018-11-22	8:30-11:30
2017-11-21	8:30-11:30	2017-11-21	14:00-17:00	2017-11-22	8:30-11:30	2017-11-27	8:30-11:30	2017-11-23	8:30-11:30
2016-11-09	8:30-11:30	2016-11-09	14:00-17:00	2016-11-10	8:30-11:30	2016-11-15	8:30-11:30	2016-11-11	8:30-11:30
2015-11-11	8:30-11:30	2015-11-11	14:00-17:00	2015-11-12	8:30-11:30	2015-11-16	8:30-11:30	2015-11-13	8:30-11:30
English		Chemistry		Biology		Entrepreneurship			
Date	Time	Date	Time	Date	Time	Date	Time		
2021-07-28	14:00-17:00	2021-07-29	8:30-11:30	2021-08-02	8:30-11:30	2021-07-29	14:00-17:00		
2019-11-14	14:00-17:00	2019-11-15	8:30-11:30	2019-11-19	8:30-11:30	2019-11-15	14:00-17:00		
2018-11-22	14:00-17:00	2018-11-23	8:30-11:30	2018-11-27	8:30-11:30	2018-11-23	14:00-17:00		
2017-10-23	14:00-17:00	2017-11-24	8:30-11:30	2017-11-28	8:30-11:30	2017-11-24	14:00-17:00		
2016-11-11	14:00-17:00	2016-11-14	8:30-11:30	2016-11-16	8:30-11:30	2016-11-14	14:00-17:00		
2015-11-13	14:00-17:00	2015-11-17	8:30-11:30	2015-11-18	8:30-11:30	2015-11-17	14:00-17:00		

Note: the table reports exam date and time of each subject students sat for from 2015 to 2021.
Source: authors' elaboration based on official documents from the Ministry of Education and the National Examination and School Inspection Authority.

Heterogeneous

Table 5: Heterogeneous effect of smart classrooms on student test scores: public schools

	Mathematics				Physics			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Exposure (months)	-0.0004	-0.0010	-0.0003	-0.0011	0.0016	0.0005	0.0016	0.0005
	(0.0016)	(0.0017)	(0.0017)	(0.0017)	(0.0018)	(0.0017)	(0.0018)	(0.0017)
Female	-0.1340***	-0.1331***	-0.1851***	-0.1843***	-0.3055***	-0.3043***	-0.3557***	-0.3547***
	(0.0083)	(0.0083)	(0.0083)	(0.0082)	(0.0092)	(0.0092)	(0.0094)	(0.0093)
R-squared	0.2984	0.3030	0.3317	0.3363	0.3817	0.3879	0.4143	0.4204
	Biology				Chemistry			
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Exposure (months)	0.0014	0.0011	0.0015	0.0010	-0.0016	-0.0018	-0.0016	-0.0019
	(0.0014)	(0.0014)	(0.0014)	(0.0014)	(0.0019)	(0.0020)	(0.0020)	(0.0020)
Female	-0.3616***	-0.3605***	-0.4100***	-0.4090***	-0.2797***	-0.2792***	-0.3238***	-0.3234***
	(0.0092)	(0.0092)	(0.0094)	(0.0093)	(0.0094)	(0.0093)	(0.0101)	(0.0100)
R-squared	0.3738	0.3799	0.4035	0.4095	0.3557	0.3613	0.3807	0.3863
	Geography				Aggregate scores			
	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)
Exposure (months)	0.0040***	0.0033**	0.0041***	0.0033**	0.0010	0.0004	0.0011	0.0003
	(0.0015)	(0.0014)	(0.0015)	(0.0015)	(0.0015)	(0.0015)	(0.0015)	(0.0015)
Female	-0.4705***	-0.4696***	-0.5170***	-0.5162***	-0.3441***	-0.3431***	-0.3980***	-0.3971***
	(0.0098)	(0.0098)	(0.0103)	(0.0102)	(0.0092)	(0.0092)	(0.0094)	(0.0094)
R-squared	0.4104	0.4154	0.4368	0.4418	0.4296	0.4336	0.4669	0.4709
School FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Exam year FE	Yes	No	Yes	No	Yes	No	Yes	No
YOB FE	No	No	Yes	Yes	No	No	Yes	Yes
District × Year FE	No	Yes	No	Yes	No	Yes	No	Yes
Observations	122926	122926	122924	122924	122926	122926	122924	122924

Note: dependent variables are the standardized grade points of the five science subjects done in the lower secondary school final national exam and the aggregate grade. The grades are standardized for each exam year. The exposure stands for the number of months each student was exposed to the smart classroom programme prior to sitting the national exam. Standard errors are clustered at school level and reported in parentheses. * significant at 10 per cent level; ** significant at 5 per cent level; *** significant at 1 per cent level.

Table 6: Heterogeneous effect of smart classrooms on test scores: public boarding schools

	Mathematics				Physics			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Exposure (months)	0.0001	0.0002	0.0002	0.0002	0.0019*	0.0019*	0.0020*	0.0019*
	(0.0010)	(0.0009)	(0.0010)	(0.0010)	(0.0011)	(0.0011)	(0.0011)	(0.0011)
x Public-Boarding	0.0107***	0.0101***	0.0102***	0.0095***	0.0093***	0.0097***	0.0087***	0.0091***
	(0.0024)	(0.0022)	(0.0024)	(0.0022)	(0.0030)	(0.0029)	(0.0030)	(0.0029)
Female	-0.1328***	-0.1328***	-0.1851***	-0.1851***	-0.2971***	-0.2972***	-0.3480***	-0.3482***
	(0.0051)	(0.0051)	(0.0051)	(0.0051)	(0.0057)	(0.0057)	(0.0058)	(0.0058)
R-squared	0.3452	0.3472	0.3773	0.3794	0.4428	0.4450	0.4734	0.4756
	Biology				Chemistry			
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Exposure (months)	0.0018*	0.0014	0.0019**	0.0015	0.0006	0.0006	0.0006	0.0006
	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0011)	(0.0011)	(0.0011)	(0.0011)
x Public-Boarding	0.0061***	0.0062***	0.0056***	0.0058***	0.0085***	0.0081***	0.0079***	0.0075***
	(0.0017)	(0.0018)	(0.0017)	(0.0018)	(0.0027)	(0.0027)	(0.0027)	(0.0026)
Female	-0.3472***	-0.3469***	-0.3968***	-0.3967***	-0.2682***	-0.2682***	-0.3123***	-0.3123***
	(0.0060)	(0.0060)	(0.0061)	(0.0061)	(0.0057)	(0.0057)	(0.0061)	(0.0060)
R-squared	0.4261	0.4283	0.4549	0.4571	0.4208	0.4228	0.4440	0.4460
	Geography				Aggregate scores			
	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)
Exposure (months)	0.0026***	0.0028***	0.0027***	0.0028***	0.0015*	0.0015*	0.0016*	0.0015*
	(0.0009)	(0.0010)	(0.0009)	(0.0010)	(0.0008)	(0.0009)	(0.0009)	(0.0009)
x Public-Boarding	0.0079***	0.0078***	0.0075***	0.0074***	0.0091***	0.0089***	0.0085***	0.0084***
	(0.0021)	(0.0020)	(0.0022)	(0.0020)	(0.0022)	(0.0022)	(0.0022)	(0.0021)
Female	-0.4630***	-0.4628***	-0.5097***	-0.5097***	-0.3349***	-0.3348***	-0.3895***	-0.3895***
	(0.0064)	(0.0064)	(0.0066)	(0.0066)	(0.0058)	(0.0058)	(0.0059)	(0.0059)
R-squared	0.4567	0.4588	0.4820	0.4841	0.4912	0.4927	0.5261	0.5275
School FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Exam year FE	Yes	No	Yes	No	Yes	No	Yes	No
YOB FE	No	No	Yes	Yes	No	No	Yes	Yes
District $\times$ Year FE	No	Yes	No	Yes	No	Yes	No	Yes
Observations	324822	324822	324821	324821	324822	324822	324821	324821

Note: dependent variables are the standardized grade points of the five science subjects done in the lower secondary school final national exam and the aggregate grade. The grades are standardized for each exam year. The exposure stands for the number of months each student was exposed to the smart classroom programme prior to sitting for national exam. Standard errors are clustered at school level and reported in parentheses. * significant at 10 per cent level; ** significant at 5 per cent level; *** significant at 1 per cent level.

Table 7: Heterogeneous effect of smart classrooms on test scores: government-aided schools

	Mathematics				Physics			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Exposure (months)	0.0023*	0.0021*	0.0023*	0.0021*	0.0041***	0.0045***	0.0040***	0.0044***
	(0.0013)	(0.0012)	(0.0013)	(0.0013)	(0.0014)	(0.0014)	(0.0014)	(0.0014)
Female	-0.1336***	-0.1334***	-0.1866***	-0.1865***	-0.2940***	-0.2942***	-0.3451***	-0.3455***
	(0.0066)	(0.0066)	(0.0066)	(0.0066)	(0.0074)	(0.0074)	(0.0074)	(0.0074)
R-squared	0.3688	0.3721	0.4004	0.4038	0.4773	0.4806	0.5067	0.5099
	Biology				Chemistry			
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Exposure (months)	0.0039***	0.0037***	0.0038***	0.0036***	0.0038***	0.0040***	0.0037***	0.0038***
	(0.0013)	(0.0013)	(0.0013)	(0.0013)	(0.0013)	(0.0013)	(0.0013)	(0.0013)
Female	-0.3393***	-0.3393***	-0.3894***	-0.3896***	-0.2642***	-0.2643***	-0.3081***	-0.3082***
	(0.0080)	(0.0079)	(0.0081)	(0.0081)	(0.0074)	(0.0075)	(0.0078)	(0.0078)
R-squared	0.4587	0.4614	0.4867	0.4893	0.4578	0.4605	0.4799	0.4825
	Geography				Aggregate scores			
	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)
Exposure (months)	0.0033**	0.0042***	0.0033**	0.0042***	0.0038***	0.0040***	0.0037***	0.0039***
	(0.0013)	(0.0013)	(0.0013)	(0.0013)	(0.0011)	(0.0011)	(0.0011)	(0.0012)
Female	-0.4567***	-0.4567***	-0.5034***	-0.5037***	-0.3304***	-0.3304***	-0.3853***	-0.3854***
	(0.0083)	(0.0083)	(0.0086)	(0.0086)	(0.0075)	(0.0075)	(0.0076)	(0.0076)
R-squared	0.4851	0.4882	0.5097	0.5129	0.5251	0.5272	0.5585	0.5605
School FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Exam year FE	Yes	No	Yes	No	Yes	No	Yes	No
YOB FE	No	No	Yes	Yes	No	No	Yes	Yes
District $\times$ Year FE	No	Yes	No	Yes	No	Yes	No	Yes
Observations	188455	188455	188455	188455	188455	188455	188455	188455

Note: dependent variables are the standardized grade points of the five science subjects done in the lower secondary school final national exam and the aggregate grade. The grades are standardized for each exam year. The exposure stands for the number of months each student was exposed to the smart classroom programme prior to sitting the national exam. Standard errors are clustered at school level and reported in parentheses. * significant at 10 per cent level; ** significant at 5 per cent level; *** significant at 1 per cent level.

Table 8: Heterogeneous effect of smart classrooms on test scores: ‘nine-twelve-years’ schools

	Mathematics				Physics			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Exposure (months)	-0.0002	-0.0003	0.0001	-0.0002	0.0001	0.0001	0.0005	0.0003
	(0.0010)	(0.0009)	(0.0010)	(0.0010)	(0.0011)	(0.0011)	(0.0011)	(0.0011)
Female	-0.1239***	-0.1234***	-0.1801***	-0.1797***	-0.2730***	-0.2728***	-0.3275***	-0.3273***
	(0.0055)	(0.0055)	(0.0055)	(0.0055)	(0.0059)	(0.0059)	(0.0061)	(0.0061)
R-squared	0.1001	0.1033	0.1500	0.1533	0.1305	0.1344	0.1842	0.1881
	Biology				Chemistry			
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Exposure (months)	0.0011	0.0008	0.0013	0.0009	-0.0002	-0.0004	-0.0000	-0.0003
	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0011)	(0.0010)	(0.0011)	(0.0010)
Female	-0.3334***	-0.3333***	-0.3868***	-0.3867***	-0.2493***	-0.2491***	-0.2945***	-0.2943***
	(0.0065)	(0.0065)	(0.0067)	(0.0067)	(0.0058)	(0.0058)	(0.0063)	(0.0063)
R-squared	0.1411	0.1447	0.1893	0.1928	0.1223	0.1254	0.1638	0.1669
	Geography				Aggregate scores			
	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)
Exposure (months)	0.0017*	0.0018*	0.0020**	0.0020**	0.0005	0.0004	0.0008	0.0006
	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0009)	(0.0009)	(0.0009)	(0.0009)
Female	-0.4599***	-0.4597***	-0.5112***	-0.5111***	-0.3201***	-0.3198***	-0.3786***	-0.3783***
	(0.0070)	(0.0070)	(0.0073)	(0.0073)	(0.0062)	(0.0062)	(0.0064)	(0.0064)
R-squared	0.1710	0.1740	0.2150	0.2181	0.1450	0.1476	0.2113	0.2139
School FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Exam year FE	Yes	No	Yes	No	Yes	No	Yes	No
YOB FE	No	No	Yes	Yes	No	No	Yes	Yes
District $\times$ Year FE	No	Yes	No	Yes	No	Yes	No	Yes
Observations	264392	264392	264391	264391	264392	264392	264391	264391

Note: dependent variables are the standardized grade points of the five science subjects done in the lower secondary school final national exam and the aggregate grade. The grades are standardized for each exam year. The exposure stands for the number of months each student was exposed to the smart classroom programme prior to sitting the national exam. Standard errors are clustered at school level and reported in parentheses. * significant at 10 per cent level; ** significant at 5 per cent level; *** significant at 1 per cent level.

Table 9: Heterogeneous effect of smart classrooms on test scores: boarding schools

	Mathematics				Physics			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Exposure (months)	0.0015	0.0040	0.0011	0.0035	0.0100***	0.0123***	0.0097***	0.0119***
	(0.0032)	(0.0032)	(0.0033)	(0.0032)	(0.0033)	(0.0029)	(0.0033)	(0.0029)
Female	-0.1806***	-0.1809***	-0.2147***	-0.2153***	-0.4207***	-0.4204***	-0.4557***	-0.4557***
	(0.0128)	(0.0128)	(0.0124)	(0.0125)	(0.0138)	(0.0138)	(0.0134)	(0.0135)
R-squared	0.3261	0.3384	0.3438	0.3561	0.4317	0.4474	0.4501	0.4652
	Biology				Chemistry			
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Exposure (months)	0.0080***	0.0079***	0.0076**	0.0075**	0.0040	0.0031	0.0036	0.0026
	(0.0030)	(0.0030)	(0.0031)	(0.0029)	(0.0046)	(0.0038)	(0.0047)	(0.0038)
Female	-0.4182***	-0.4167***	-0.4504***	-0.4487***	-0.3646***	-0.3661***	-0.4028***	-0.4040***
	(0.0140)	(0.0140)	(0.0140)	(0.0140)	(0.0158)	(0.0155)	(0.0158)	(0.0154)
R-squared	0.4217	0.4332	0.4380	0.4495	0.3748	0.3883	0.3901	0.4033
	Geography				Aggregate scores			
	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)
Exposure (months)	0.0057**	0.0069**	0.0054**	0.0065*	0.0065**	0.0077***	0.0061**	0.0072***
	(0.0026)	(0.0033)	(0.0027)	(0.0033)	(0.0027)	(0.0027)	(0.0027)	(0.0028)
Female	-0.4791***	-0.4790***	-0.5058***	-0.5057***	-0.4114***	-0.4113***	-0.4483***	-0.4482***
	(0.0147)	(0.0146)	(0.0153)	(0.0152)	(0.0137)	(0.0136)	(0.0136)	(0.0135)
R-squared	0.4570	0.4705	0.4689	0.4824	0.4722	0.4831	0.4920	0.5027
School FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Exam year FE	Yes	No	Yes	No	Yes	No	Yes	No
YOB FE	No	No	Yes	Yes	No	No	Yes	Yes
District $\times$ Year FE	No	Yes	No	Yes	No	Yes	No	Yes
No. Years	6	6	6	6	6	6	6	6
Observations	62456	62456	62451	62451	62456	62456	62451	62451

Note: dependent variables are the standardized grade points of the five science subjects done in the lower secondary school final national exam and the aggregate grade. The grades are standardized for each exam year. The exposure stands for the number of months each student was exposed to the smart classroom programme prior to sitting the national exam. Standard errors are clustered at school level and reported in parentheses. * significant at 10 per cent level; ** significant at 5 per cent level; *** significant at 1 per cent level.

Mechanisms

Table 10: Degree of computer access and test scores: student-computer ratio

	Maths	Physics	Biology	Chemistry	Geography	Aggregate scores
	(1)	(2)	(3)	(4)	(5)	(6)
Female	-0.1853***	-0.3483***	-0.3967***	-0.3124***	-0.5098***	-0.3896***
	(0.0051)	(0.0058)	(0.0061)	(0.0060)	(0.0066)	(0.0059)
Student-computer ratio	-0.0383**	-0.0196	-0.0248*	0.0062	-0.0198	-0.0228*
	(0.0151)	(0.0157)	(0.0148)	(0.0146)	(0.0138)	(0.0129)
Exposure (months)	0.0043***	0.0078***	0.0055***	0.0049***	0.0074***	0.0064***
	(0.0013)	(0.0015)	(0.0013)	(0.0015)	(0.0014)	(0.0013)
× Student-computer ratio	-0.0017*	-0.0037***	-0.0023**	-0.0032***	-0.0027***	-0.0028***
	(0.0009)	(0.0012)	(0.0009)	(0.0011)	(0.0010)	(0.0010)
School FE	Yes	Yes	Yes	Yes	Yes	Yes
District-year FE	Yes	Yes	Yes	Yes	Yes	Yes
YOB FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.3791	0.4756	0.4571	0.4459	0.4841	0.5274
Observations	324821	324821	324821	324821	324821	324821

Note: dependent variables are the standardized grade points of the five science subjects done in the lower secondary school final national exam and the aggregate grade. The grades are standardized for each exam year. The exposure stands for the number of months each student was exposed to the smart classroom programme prior to sitting the national exam. Standard errors are clustered at school level and reported in parentheses. * significant at 10 per cent level; ** significant at 5 per cent level; *** significant at 1 per cent level.

Table 11: Smart classroom and student test scores: role of female school manager

	Mathematics				Physics			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Female school manager	0.0083	0.0166	0.0083	0.0164	-0.0021	0.0034	-0.0023	0.0031
	(0.0114)	(0.0110)	(0.0113)	(0.0110)	(0.0123)	(0.0116)	(0.0121)	(0.0115)
Exposure (months)	0.0013	0.0017	0.0012	0.0016	0.0030**	0.0034***	0.0029**	0.0032***
	(0.0011)	(0.0011)	(0.0011)	(0.0011)	(0.0012)	(0.0012)	(0.0012)	(0.0012)
Interacted with SM	0.0008	0.0002	0.0008	0.0002	0.0011	0.0005	0.0011	0.0005
	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0009)	(0.0009)	(0.0009)	(0.0009)
R-squared	0.3481	0.3511	0.3765	0.3794	0.4232	0.4262	0.4466	0.4495
	Biology				Chemistry			
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Female school manager	-0.0016	0.0054	-0.0017	0.0051	-0.0028	0.0058	-0.0028	0.0057
	(0.0121)	(0.0119)	(0.0119)	(0.0117)	(0.0129)	(0.0125)	(0.0127)	(0.0124)
Exposure (months)	0.0025**	0.0023**	0.0025**	0.0022**	0.0019	0.0020	0.0018	0.0017
	(0.0011)	(0.0011)	(0.0011)	(0.0011)	(0.0013)	(0.0013)	(0.0012)	(0.0012)
Interacted with SM	0.0012	0.0010	0.0012	0.0009	0.0006	0.0001	0.0006	0.0001
	(0.0009)	(0.0008)	(0.0008)	(0.0008)	(0.0009)	(0.0008)	(0.0009)	(0.0008)
R-squared	0.4007	0.4036	0.4218	0.4247	0.3995	0.4023	0.4171	0.4199
	Geography				Aggregate scores			
	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)
Female school manager	-0.0045	0.0019	-0.0045	0.0018	-0.0003	0.0075	-0.0004	0.0073
	(0.0120)	(0.0118)	(0.0119)	(0.0117)	(0.0101)	(0.0096)	(0.0098)	(0.0095)
Exposure (months)	0.0038***	0.0042***	0.0038***	0.0041***	0.0027***	0.0029***	0.0026***	0.0027***
	(0.0011)	(0.0011)	(0.0011)	(0.0011)	(0.0010)	(0.0010)	(0.0010)	(0.0010)
Interacted with SM	-0.0000	-0.0004	-0.0000	-0.0004	0.0009	0.0004	0.0009	0.0004
	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0007)	(0.0007)	(0.0007)
R-squared	0.4078	0.4107	0.4241	0.4269	0.4710	0.4731	0.4974	0.4994
School FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Exam year FE	Yes	No	Yes	No	Yes	No	Yes	No
YOB FE	No	No	Yes	Yes	No	No	Yes	Yes
District $\times$ Year FE	No	Yes	No	Yes	No	Yes	No	Yes
Observations	244412	244412	244411	244411	244412	244412	244411	244411

Note: dependent variables are the standardized test scores (grades) of the five science subjects conducted in the final national exam at the lower secondary school. The exposure stands for the number of months each student was exposed to the smart classroom programme prior to sitting the national exam. Standard errors are clustered at school level and reported in parentheses. * significant at 10 per cent level; ** significant at 5 per cent level; *** significant at 1 per cent level.

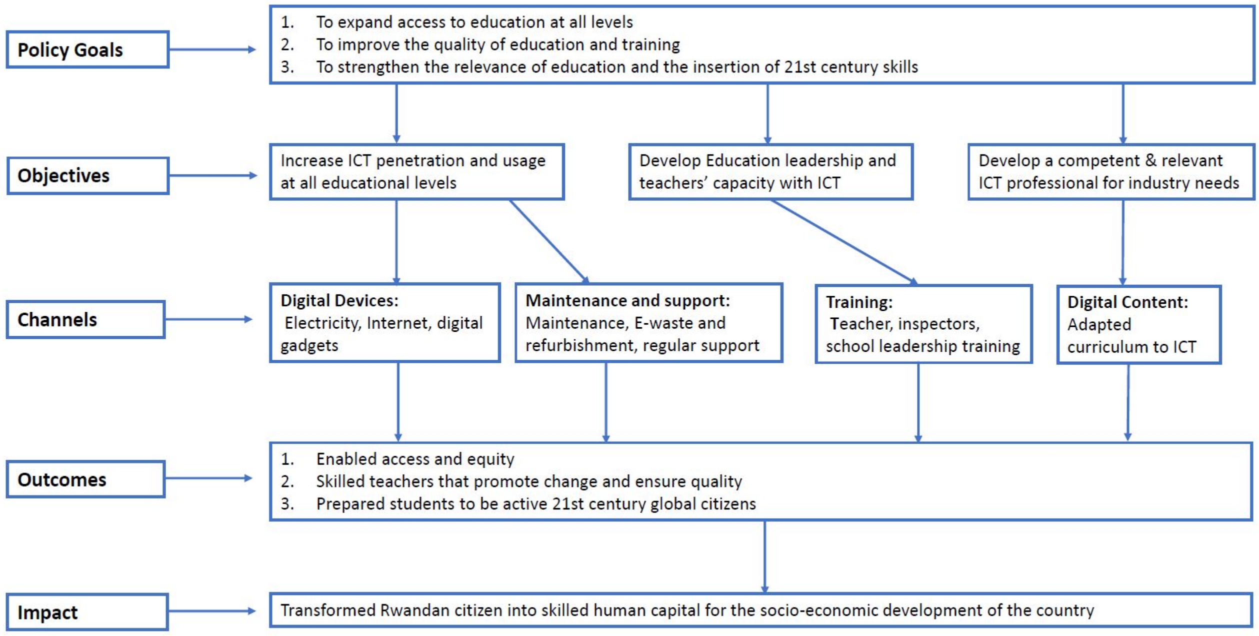
Table 12: Smart classroom and student test scores: role of female DoS

	Mathematics				Physics			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Female DoS	-0.0424*	-0.0238	-0.0364	-0.0162	-0.0564**	-0.0524**	-0.0502**	-0.0447**
	(0.0227)	(0.0216)	(0.0224)	(0.0215)	(0.0244)	(0.0231)	(0.0237)	(0.0224)
Exposure (months)	0.0006	0.0012	0.0007	0.0012	0.0024**	0.0028**	0.0024**	0.0027**
	(0.0011)	(0.0011)	(0.0011)	(0.0011)	(0.0012)	(0.0011)	(0.0012)	(0.0011)
Interacted with DoS	0.0041***	0.0026**	0.0037***	0.0022*	0.0046***	0.0037***	0.0042***	0.0031**
	(0.0013)	(0.0012)	(0.0013)	(0.0012)	(0.0014)	(0.0014)	(0.0014)	(0.0013)
R-squared	0.3483	0.3511	0.3766	0.3794	0.4234	0.4264	0.4468	0.4496
	Biology				Chemistry			
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Female DoS	-0.0263	-0.0224	-0.0210	-0.0160	-0.0406	-0.0342	-0.0343	-0.0265
	(0.0212)	(0.0215)	(0.0208)	(0.0212)	(0.0267)	(0.0255)	(0.0261)	(0.0249)
Exposure (months)	0.0024**	0.0023**	0.0025**	0.0023**	0.0014	0.0014	0.0014	0.0013
	(0.0011)	(0.0011)	(0.0011)	(0.0011)	(0.0012)	(0.0012)	(0.0012)	(0.0012)
Interacted with DoS	0.0026**	0.0019	0.0024**	0.0015	0.0030*	0.0026*	0.0026*	0.0021
	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0016)	(0.0014)	(0.0015)	(0.0014)
R-squared	0.4007	0.4036	0.4218	0.4247	0.3997	0.4024	0.4172	0.4199
	Geography				Aggregate scores			
	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)
Female DoS	-0.0599***	-0.0489**	-0.0552**	-0.0432*	-0.0484**	-0.0385*	-0.0424**	-0.0311
	(0.0229)	(0.0233)	(0.0224)	(0.0229)	(0.0214)	(0.0210)	(0.0208)	(0.0205)
Exposure (months)	0.0029***	0.0033***	0.0029***	0.0033***	0.0021**	0.0024**	0.0021**	0.0023**
	(0.0011)	(0.0011)	(0.0011)	(0.0011)	(0.0009)	(0.0010)	(0.0009)	(0.0010)
Interacted with DoS	0.0034***	0.0025**	0.0032***	0.0022*	0.0039***	0.0029**	0.0035***	0.0024**
	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0011)
R-squared	0.4080	0.4108	0.4242	0.4270	0.4712	0.4731	0.4976	0.4995
School FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Exam year FE	Yes	No	Yes	No	Yes	No	Yes	No
YOB FE	No	No	Yes	Yes	No	No	Yes	Yes
District $\times$ Year FE	No	Yes	No	Yes	No	Yes	No	Yes
Observations	244412	244412	244411	244411	244412	244412	244411	244411

Note: dependent variables are the standardized test scores (grades) of the five science subjects conducted in the final national exam at the lower secondary school. The exposure stands for the number of months each student was exposed to the smart classroom programme prior to sitting the national exam. Standard errors are clustered at school level and reported in parentheses. * significant at 10 per cent level; ** significant at 5 per cent level; *** significant at 1 per cent level.

Figures

Figure 1: Theory of change



Source: designed by the authors, based on MINEDUC (2016).

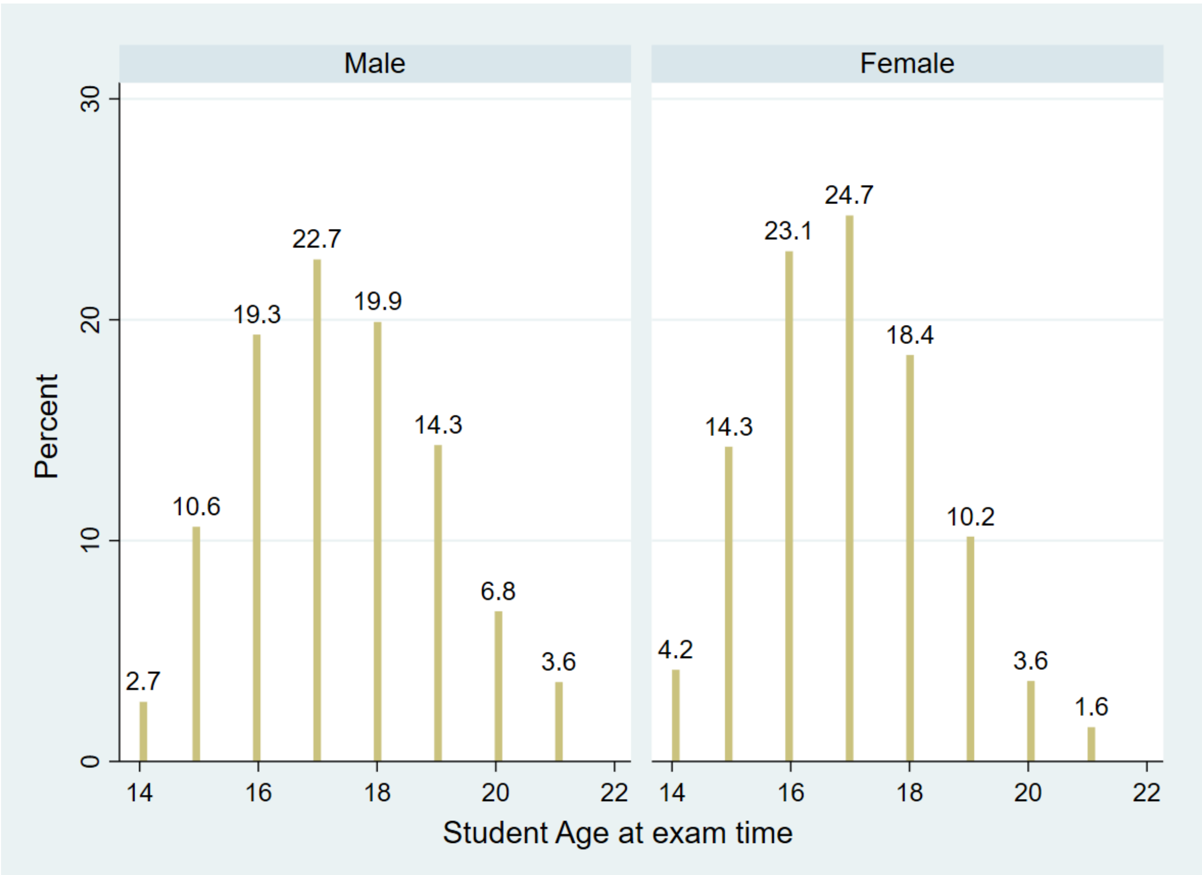
Figure 2: Smart classroom and seating arrangement

Note: the figure shows a three-dimension design of a smart classroom (SCM); 9x10 metres with 50 laptops.
Source: SCM design document (REB 2018). Reproduced with permission.

Figure 3: Students in a smart classroom

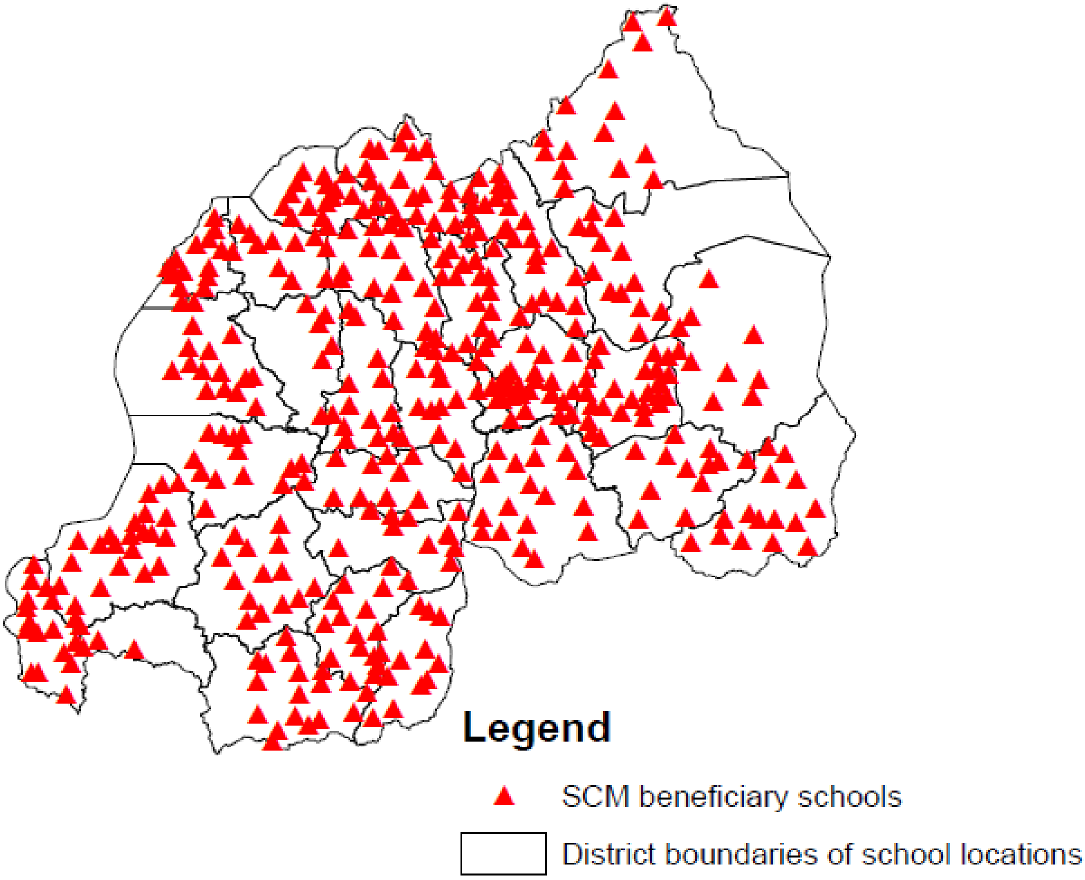
Note: the figure provides an example of students in an SCM. Picture taken on 3 July 2019 at GS Kigali at IDP Model Village.
Source: Ministry of Education's website, homepage. Reproduced with permission.

Figure 4: Students' age distribution at lower-secondary national exam time



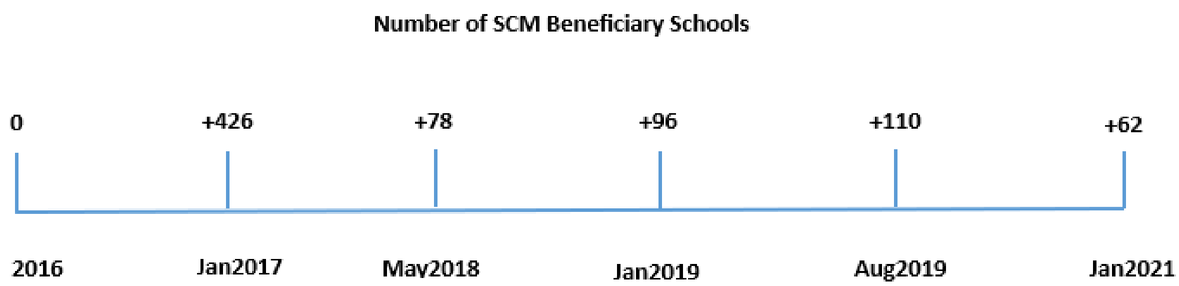
Source: computed by the authors based on the students' demographic records from NESA; see Section 3.2 for more details.

Figure 5: SCM-programme beneficiary schools



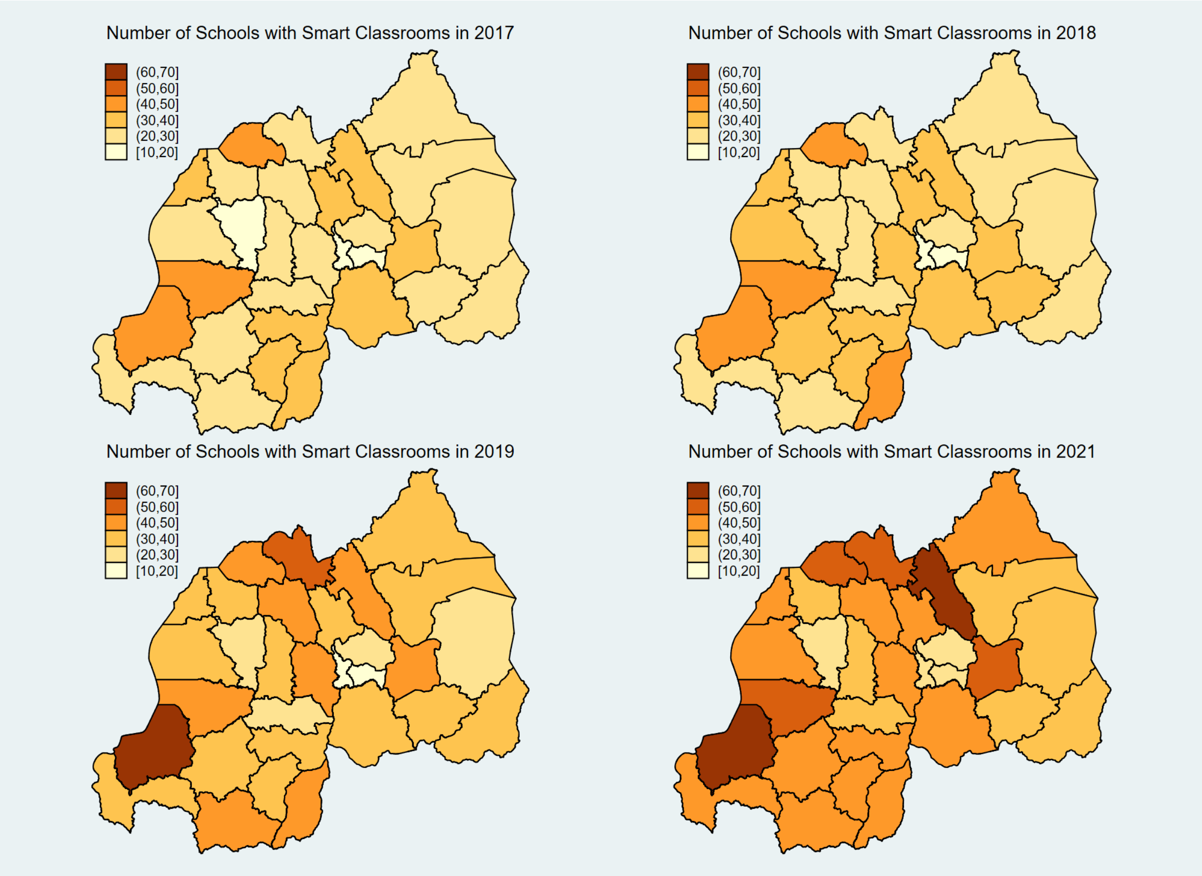
Note: the figure gives SCM-programme beneficiary schools' locations, Jan2017–July2021.
Source: constructed by the authors based on school location records from NESA; see Section 3.2 for more details.

Figure 6: Timeline for the smart classroom programme



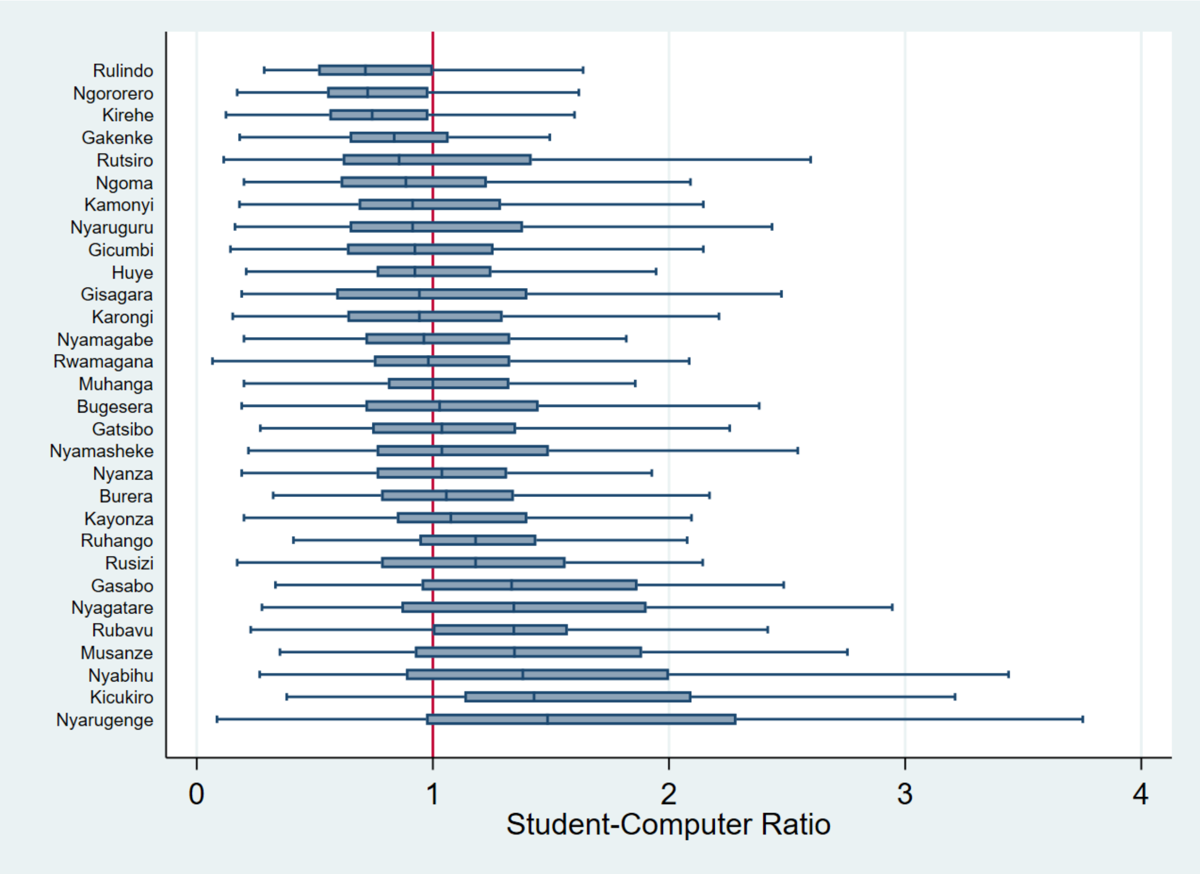
Note: the figure provides the number of SCM beneficiary schools between Jan2017 and July2021 in the country.
Source: computed by the authors based on the SCM implementation records from REB; see Section 3.2 for more details.

Figure 7: Distribution of schools with smart classrooms across districts in Rwanda (2017–21)



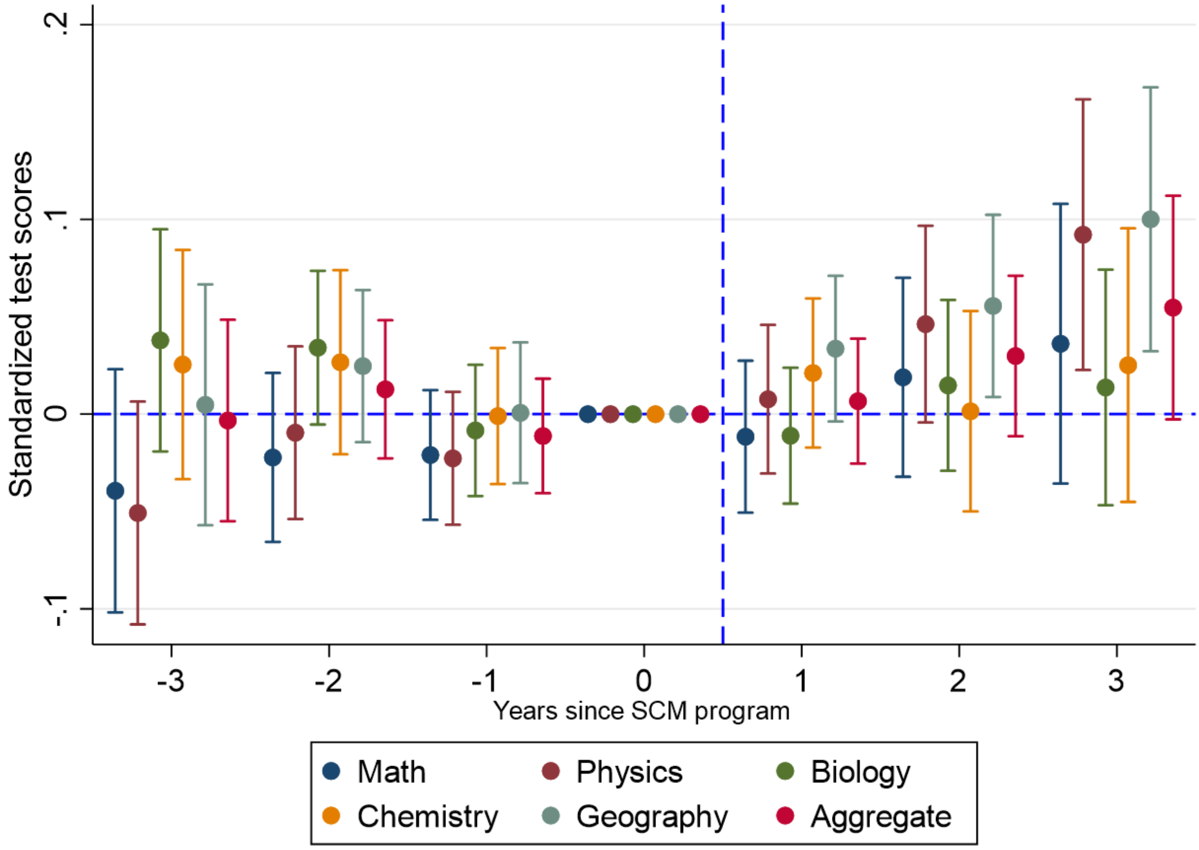
Note: the figure shows the number of schools with smart classrooms in the country.
Source: computed by the authors based on the SCM implementation records from REB; see Section 3.2 for more details.

Figure 8: Student-computer ratio in year 3 of lower secondary schools



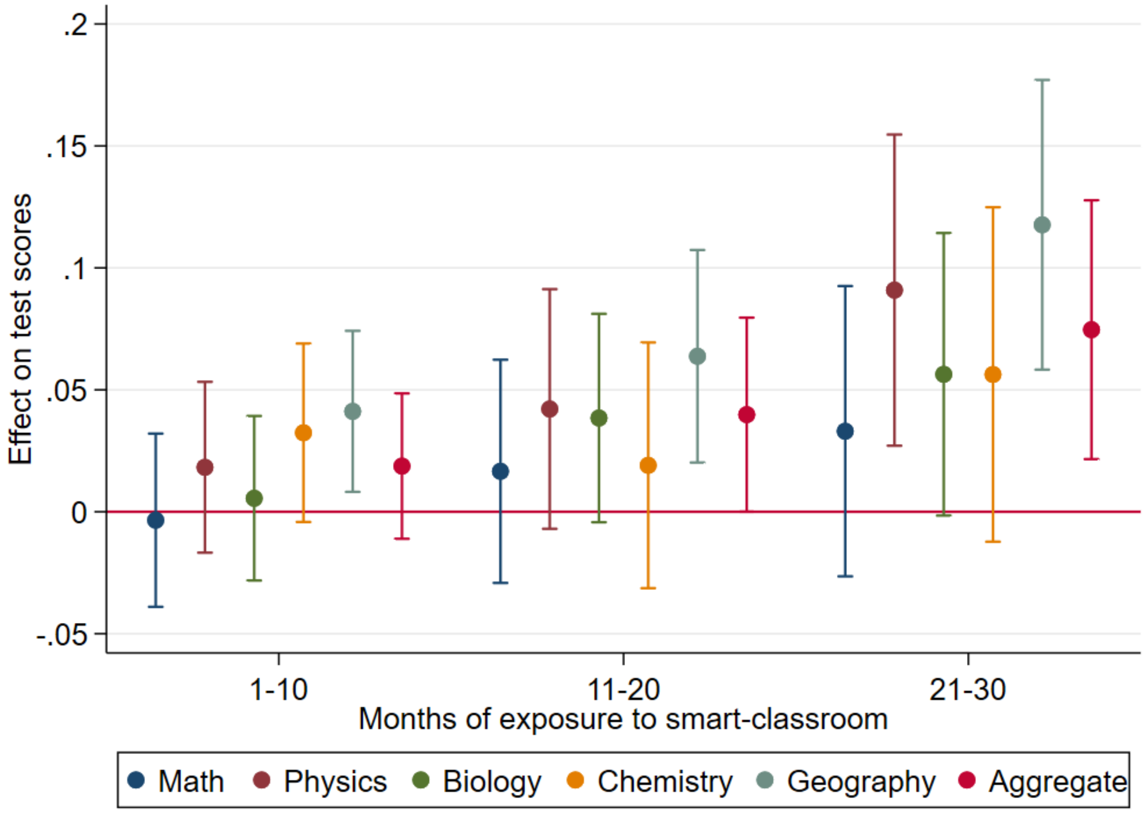
Note: the figure shows various student-computer ratios across districts in Rwanda.
Source: computed by the authors based on the SCM implementation records from REB and students' demographics from NESA. See Section 3.2 for more details.

Figure 9: Event study: SCM programme and student exam scores



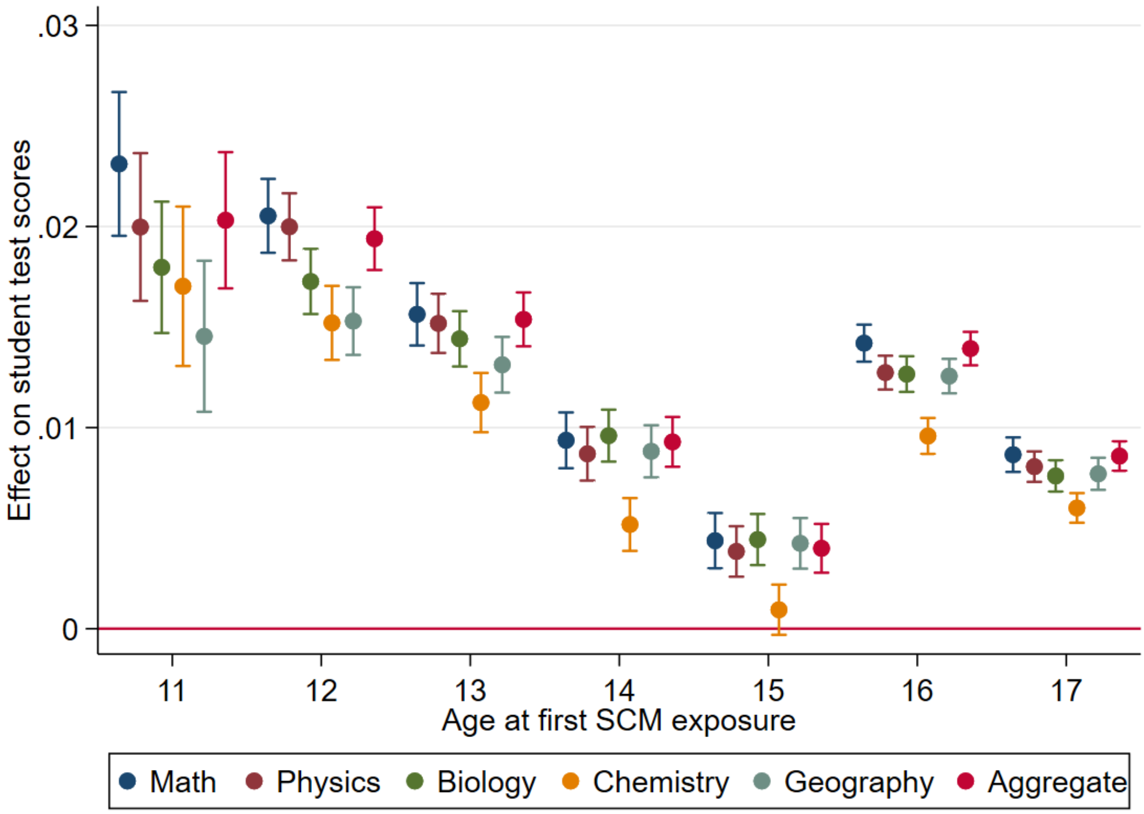
Note: this figure provides the coefficient estimates and their 95% confidence intervals from a regression of students' test scores on dummy variables for the years before and after the start of SCM programme in their respective schools. The specification includes controls for gender of student, year of birth, school fixed effects, and district-by-exam-year fixed effects.
Source: authors' construction.

Figure 10: Heterogeneous effect of SCM exposure on student grades



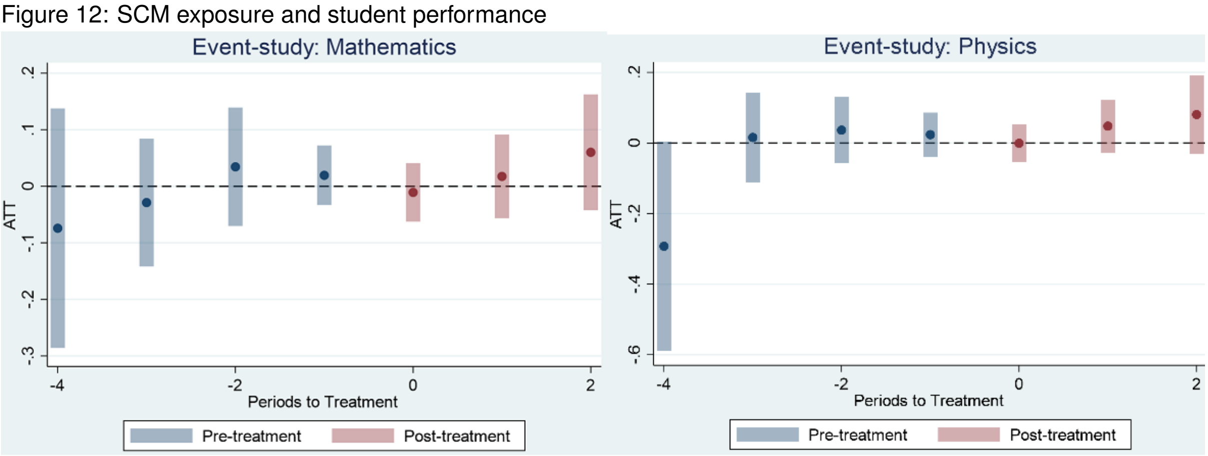
Note: the figure shows various estimated coefficients of the smart classroom exposure on student test grade points, at a 95% confidence interval. The control group is the non-exposed students.
Source: authors' construction.

Figure 11: Effects of smart classroom exposure on test scores by student age



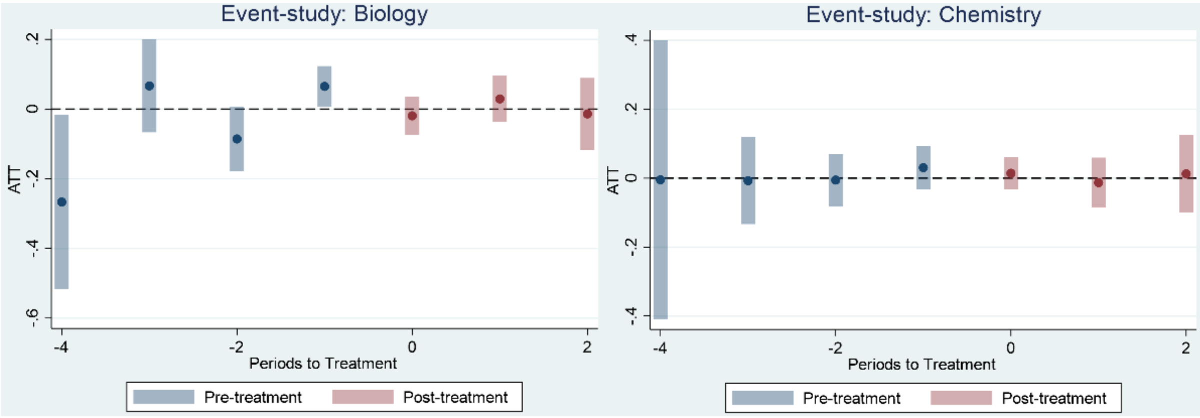
Note: the figure exhibits various estimated coefficients of the smart classroom exposure on test scores in the science subjects during the national exam, at a 95% confidence interval. The control group is the students aged 17–21 at the time of the introduction of SCM.
Source: authors' construction.

Figure 12: SCM exposure and student performance



Note: the figure exhibits various estimated coefficients of the SCM exposure on the multiple schools (groups), and multiple periods (2017/19) at a 95% CI, based on the DID approach by Callaway and Sant'Anna (2021).
Source: authors' construction.

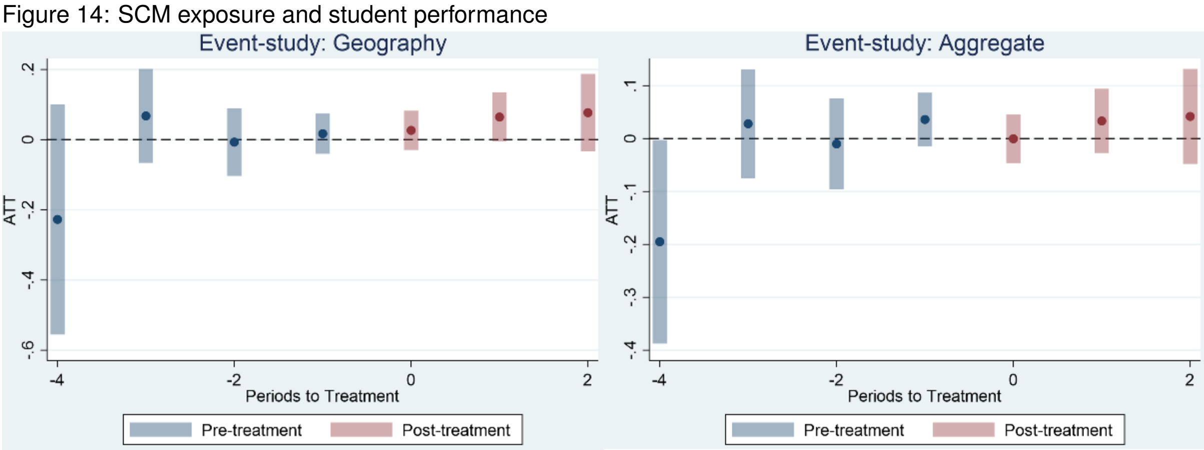
Figure 13: SCM exposure and student performance



Note: the figure exhibits various estimated coefficients of the SCM exposure on the multiple schools (groups), and multiple periods (2017/19) at a 95% CI, based on the DID approach by Callaway and Sant'Anna (2021).

Source: authors' construction.

Figure 14: SCM exposure and student performance



Note: the figure exhibits various estimated coefficients of the SCM exposure on the multiple schools (groups), and multiple periods (2017/19) at a 95% CI, based on the DID approach by Callaway and Sant'Anna (2021).

Source: authors' construction.