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Private beats public

A flexible value-added model with Tanzanian school switchers

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Abstract: This paper estimates a private school learning premium in Tanzania by implementing a flexible value-added model with unique administrative data on exam scores. The dataset covers 635,000 secondary school students with information on both their primary and lower secondary school exam records, allowing three out of four assumptions imposed in standard value-added models to be relaxed. The preferred coefficient estimate suggests private secondary schools, on average, increase student exam scores at national exams by 0.45 standard deviations after two years of secondary schooling. Standard value-added models are found to bias the learning premium upward. An instrumental variable model confirms a positive causal learning premium. Subject-specific learning premiums for Kiswahili, English, and mathematics are 0.28, 0.39, and 0.50 standard deviations, respectively.

Keywords: achievement gap, education, human capital development, mixed markets, private school

JEL classification: I20, I21, H44, I24, O15

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1 Introduction

Do students learn more in private schools compared to public schools? While this question continues to be raised in developed and developing countries, the potential contribution of privately run schools has been noted for low-income countries in particular. This is for two main reasons. First, in these contexts, popular models of private schools have been shown to deliver education at a similar or lower per-pupil cost than public schools (Alderman et al., 2001; Andrabi et al., 2008; Bold et al., 2013; Jimenez et al., 1991; Lassibille et al., 2000; Muralidharan and Sundararaman, 2015; Ngetich et al., 2014; Psacharopoulos, 1987; Schirmer, 2010; Tooley et al., 2011). Reasons include lower teacher salaries as private schools may hire from a different pool of applicants, lower prices for food and equipment due to better incentives to negotiate, and lower costs of renting buildings due to lack of regulations. Thus, based on expenses, one should not automatically expect private schools to outperform public schools.

Second, private schools are generally found to improve student test scores.[1] With data from the state of Andhra Pradesh in India, Singh (2015) employs a value-added model accounting for unobserved ability by including lagged Raven's test scores. The author finds a positive private school learning premium in English and Telugu (the local language) for 8–10-year-old students, and in mathematics and Telugu for 15-year-old students. The author further finds that rural areas have a larger private school learning premium compared to urban areas. With data on Pakistani primary school students, Andrabi et al. (2011) study the effects of measurement error and unobserved ability when estimating a private school learning premium and a learning persistence parameter. They find measurement error biases the persistence parameter downward, while omitting unobserved ability biases the persistence parameter upward. The effect on the coefficient estimate associated with attending private school is ambiguous. In addition to the methodological contribution, the authors estimate a private school learning premium of 0.25 of a standard deviation in test scores per year, with a substantially larger effect in the first year of switching to a private school.

Angrist et al. (2002) study the effects on learning and probability of repeating a grade from allocation of private school vouchers in Columbia. The authors find that after three years of private schooling, lottery winners were less likely to repeat grades, and they scored 0.21 of a standard deviation higher on tests compared to lottery losers. In India, Muralidharan and Sundararaman (2015) find that private schools are cheaper to operate than public schools; on average, costs per student were one-third in private schools relative to the costs in public schools. In terms of learning, the authors estimate both the impact of winning a private school voucher, and the average treatment on the treated (ATT) effect for different subjects. The ATT effect in Hindi test scores is estimated to be 1.07 of a standard deviation four years after the lottery took place. The authors find a smaller effect in English test scores of 0.23 of a standard deviation after four years, while test scores in Telugu, mathematics, science, and social studies were insignificantly affected by private school enrolment.

While a positive impact of private schools on learning outcomes is generally acknowledged in the literature, substantial caveats remain (Day Ashley et al., 2014). Most importantly, the applied methodologies most often rely on cross-sectional ordinary least squares (OLS) models, thereby assuming past school inputs have no effect on test scores. Another methodology employed is the standard value-added model using lagged achievement as an explanatory variable for current achievement. This model, however, needs to make four key assumptions, of which some could be critical for identification. In addition to the methodological weaknesses, the magnitude of the estimated learning premiums varies substantially, evidence is to a large extent based on data from South Asia, and subject-specific learning premiums differ heavily both between and within studies.

[1] Throughout this paper, learning gains from attending a private school are referred to as the private school learning premium.

The current paper makes four key contributions to the literature. It: (1) estimates a flexible value-added model relaxing three out of four commonly imposed assumptions in standard value-added models; (2) provides evidence for a geographical area with relatively little existing evidence; (3) estimates an instrumental variable model to determine causality; and (4) examines subject-specific private school learning premiums. Specifically, the proposed value-added model includes a lagged school $\times$ lagged exam score $\times$ cohort fixed effect, together with a proxy for unobserved ability. This allows the model to compare students from the same primary school achieving the same primary school exam scores in the same year. The applied data source derives from Tanzanian exam records. Student exam records from the final grade of primary school are merged with exam records after two years of lower secondary school. This approach results in a database covering 635,000 secondary school students, with information on primary school exam scores and lower secondary school exam scores, which is unprecedented in the sub-Saharan African context. In robustness analyses, the paper estimates an instrumental variable (IV) model to determine whether the private school coefficient estimate is causal, a sample selection model, and subject-specific private school learning premiums.

The results provide evidence for a large private school learning premium in Tanzania. The preferred model demonstrates that attending a private secondary school, instead of a public school, leads to a 0.45 standard deviation increase in exam scores after two years of secondary schooling. An IV model confirms the positive learning premium is causal, and a Heckman sample selection model demonstrates the preferred result is highly robust to sample selection. The private school learning premiums estimated from a standard value-added model and a pooled OLS model are found to be substantially biased upward, which emphasizes the significance of employing the flexible value-added model. Subject-specific analyses find that private schools on average increase students' exam scores by 0.28, 0.39, and 0.50 standard deviations in Kiswahili, English, and mathematics, respectively.

Section 2 considers the theoretical framework in regard to the standard value-added model and the current paper's flexible value-added model. Section 3 describes the Tanzanian education system and the data at hand. Section 4 develops the methodology applied. Sections 5 and 6 present the main regression results and discuss the robustness of the results, respectively. Section 7 concludes.

2 Theoretical framework

Todd and Wolpin (2003) present a cumulative learning production function given by Equation 1. That is, a student's test score at age a is dependent on inputs at all ages up to and including age a. Under a different set of assumptions, the OLS model and the standard value-added model can be derived from this general production function.

$$T_{ija} = T_a[F_{ij}(a), S_{ij}(a), \mu_{ij0}, \varepsilon_{ij}]. \tag{1}$$

The outcome variable is the test score for student i in household j at age a. The right-hand side of the equation consists of family-supplied inputs, F, school-supplied inputs, S, a time-invariant parameter measuring unobserved ability, and an idiosyncratic error term. The impacts of these explanatory variables are initially allowed to vary for different ages.

The OLS model provides unbiased estimates as long as only current inputs and inputs constant over time affect test scores. Thus, school inputs from previous years are assumed not to influence a student's current test score. This assumption implies lagged achievement is not a relevant explanatory variable for current achievement, which is generally rejected.

When employing the standard value-added model, one needs to make four key assumptions. First, the arguments in the cumulative learning production function are additively separable. Second, the coefficients on inputs are non-age-varying. Applying these first two assumptions, the following expression for student i's test score at age a can be derived:

$$T_{ija} = F_{ija}\varphi_a + F_{ij,a-1}\varphi_{a-1} + \ldots + F_{ij1}\varphi_1 + S_{ija}\alpha_a + S_{ij,a-1}\alpha_{a-1} + \ldots + S_{ij1}\alpha_1 + \beta_a\mu_{ij0} + \varepsilon_{ija}. \quad (2)$$

Next, the lagged test score multiplied by the rate of decay parameter is subtracted on both sides of Equation 2, which gives Equation 3:

$$\begin{aligned} T_{ija} - \gamma T_{ij,a-1} = & F_{ija}\varphi_a + F_{ij,a-1}(\varphi_{a-1} - \gamma\varphi_a) + \ldots + F_{ij1}(\varphi_1 - \gamma\varphi_2) \\ & + S_{ija}\alpha_a + S_{ij,a-1}(\alpha_{a-1} - \gamma\alpha_a) + \ldots + S_{ij1}(\alpha_1 - \gamma\alpha_2) \\ & + (\beta_a - \gamma\beta_{a-1})\mu_{ij0} + \varepsilon_{ija} - \gamma\varepsilon_{ij,a-1}. \end{aligned} \quad (3)$$

In order to derive the standard value-added model, one needs to impose a third and a fourth assumption. Third, learning effects from different inputs to the learning process decay at the same rate over time. For instance, the learning effects from parental involvement and a better teacher at a specific age decay at the same rate. Fourth, the impact by unobserved ability must decay at the same rate as the effects from school and family inputs. Thus, it is assumed for every age of the student that:

$$\gamma = \frac{\varphi_{a-1}}{\varphi_a} = \frac{\alpha_{a-1}}{\alpha_a} = \frac{\beta_a}{\beta_{a-1}}. \quad (4)$$

After imposing the above-mentioned assumptions to Equation 3, the standard value-added model given by Equation 5 is derived:

$$T_{ija} = F_{ija}\varphi_a + S_{ija}\alpha_a + \gamma T_{ij,a-1} + \eta_{ija}, \quad (5)$$

where $\eta_{ija} = \varepsilon_{ija} - \gamma\varepsilon_{ij,a-1}$, φ_a identifies the effects from current family-supplied inputs, α_a identifies the effects from current school-supplied inputs, and γ is the persistence parameter measuring the rate of decay of learning effects from past inputs. As the arguments in the production function are assumed to be additively separable, unobserved ability is also assumed to have no effect on returns to inputs.

The current paper proposes a method to improve the standard value-added model by relaxing three of the four assumptions made above. Table 1 outlines the assumptions needed in the standard value-added model and in the proposed value-added model.

First, by including lagged school fixed effects into the model, previous school-supplied inputs become redundant. In Equation 3, this is equivalent to replacing previous school inputs with a lagged school fixed effect, meaning all learning effects from previous time periods are captured in the lagged school fixed effect. This model assumes students have attended the same school from start of school until age $a-1$, and students in the same school receive the same school inputs. Equation 6 presents the lagged school fixed effect model:

$$\begin{aligned} T_{ijsa} - \gamma T_{ijs,a-1} = & F_{ija}\varphi_a + F_{ij,a-1}(\varphi_{a-1} - \gamma\varphi_a) + \ldots + F_{ij1}(\varphi_1 - \gamma\varphi_2) \\ & + S_{ija}\alpha_a + \delta_{s,a-1} + (\beta_a - \gamma\beta_{a-1})\mu_{ij0} + \varepsilon_{ijsa} - \gamma\varepsilon_{ijs,a-1}, \end{aligned} \quad (6)$$

where $\delta_{s,a-1}$ is the lagged school fixed effect for each school s. The coefficient associated with current school inputs, α_a, can now be identified independently of the value of the persistence parameter, and the assumption of similar rates of decay for school- and family-supplied inputs can be dropped.

Table 1: Assumptions needed to provide unbiased coefficient estimates

Core assumptions	Standard value-added model	Flexible value-added model
Arguments in the cumulative learning production function are additively separable	✓	✗ (unobserved ability allowed to influence returns to inputs)
Coefficients on school and family inputs are non-age-varying	✓	✓
Learning effects from school and family inputs decay at the same rate over time	✓	✗
Impact of unobserved ability decays at the same rate as school and family inputs	✓	✗
Students with the same test scores in the same school at age $a-1$ attended the same school since beginning of school	✗	✓
Students with the same test scores in the same school at age $a-1$ received the same school inputs since beginning of school	✗	✓

Source: author's own.

The effect from unobserved ability is not neutralized if $\gamma \neq \beta_a/\beta_{a-1}$. Including a proxy for unobserved ability allows the rate of decay for unobserved ability to differ from the rates of decay for the inputs. Finally, in Equation 3 it may be that the αs differ for specific types of students. For instance, high-ability students may receive more attention or they may be simply better at benefiting from the given inputs. A famously known example is Glewwe et al. (2009), showing that providing free textbooks in rural Kenya only had an effect on high-ability students. That is, ability could influence the return to inputs, thereby rejecting the additive separability assumption. To counter this issue, the current paper proposes to include a lagged school $\times$ lagged achievement fixed effect into the model. This procedure ensures students are compared only to other students benefiting similarly from the same school inputs. Thus, by assuming students have attended the same school until and including age $a-1$, and students in the same school receive the same school inputs, the proposed value-added model takes the following form:

$$T_{ijsga} = F_{ija}\varphi_{a} + S_{ija}\alpha_a + \mu_{ij0}(\beta_a - \gamma\beta_{a-1}) + \theta_{sg,a-1} + \eta_{ijsga}, \tag{7}$$

where, independent of the age of the student, $\gamma = \varphi_{a-1}/\varphi_{a}$, and $\eta_{ijsga} = \varepsilon_{ijsga} - \gamma\varepsilon_{ijsg,a-1}$. Subscript g refers to achievement level, meaning $\theta_{sg,a-1}$ is a lagged school $\times$ lagged achievement fixed effect. When more than one cohort of students are available, the lagged school $\times$ lagged achievement fixed effect is replaced by a lagged school $\times$ lagged achievement $\times$ cohort fixed effect.

In the remainder of the paper, a simple OLS model, the standard value-added model (Equation 5), the school fixed effect model (Equation 6), and the flexible value-added model (Equation 7) are estimated with administrative exam records from Tanzania.

3 Context and data

3.1 Tanzanian educational context

The education system in Tanzania consists of seven years of primary school followed by four years of secondary school. Next, students have the opportunity to either continue their studies for two years of advanced secondary schooling or take a 2–3 year technical or vocational education. Students passing advanced secondary school may continue to university. The current paper focuses on the first two years of secondary education, called lower secondary.

The school system experienced a major reform in 2002, when primary school tuition fees were abolished. This led to a surge in the primary school gross enrolment rate, peaking at almost 109 per cent in 2008. The gross enrolment rate has since 2008 declined gradually, and in 2015 it reached 82 per cent (UNESCO Institute for Statistics, 2017). Public secondary schooling remained partially funded by school fees until the implementation of Tanzania's Education and Training policy in the beginning of 2016 (Human Rights Watch, 2017). In addition to the abolition of school fees in 2016, secondary schools were no longer obliged to teach in English.[2] While primary schooling has become universal in Tanzania, the share of children attending secondary school is still low. According to the World Bank's most recent data, from 2012, 56 per cent of students attending the final grade of primary school without repeating the final grade progress to secondary school (World Bank, 2018).

Private schools are substantially more widespread at the secondary school level compared to the primary school level. In 2013, 2.4 per cent of primary school students attended a private school, whereas 21.4 per cent of secondary school students attended a private school (World Bank, 2018). This phenomenon of secondary school students being more likely to attend private school is also evident in the share of schools being privately operated. In 2016, 6 per cent and 25 per cent of schools were privately operated in primary education and secondary education, respectively.

Compared to Uganda, Burundi, Rwanda, and Kenya, Tanzania has the lowest progression rate to secondary school in terms of the share of primary school students not repeating the final grade of primary school and progressing to secondary school. In 2012, the progression rate was 8 percentage points higher in Uganda, and around 19 percentage points higher in Rwanda and Burundi. There are no data available for 2012 for Kenya, but in 2014 the rate of progression was almost 100 per cent. Also, the use of private schools differs among the East African countries. While the share of students attending private schools in primary education is similar to the shares in Rwanda and Burundi, around 16 per cent of primary school students attend private schools in Uganda and Kenya. The shares of students attending private secondary schools are more similar across countries (World Bank, 2018).

3.2 Data sources

Section 2 presented a strategy that would relax three of the four key assumptions needed in standard value-added models. The proposed strategy, however, has strict requirements for the applied data source. The applied data must contain information on student lagged and present achievement, together with information on current schoolmates' lagged achievement. Furthermore, one must have information on previous schoolmates' lagged achievement, present achievement, and present school enrolment.

The current paper relies on two main data sources: (1) individual exam records from the Primary School Leaving Examination (PSLE) in 2013, 2014, and 2015; and (2) individual exam records from the Form Two National Assessment (FTNA) in 2015, 2016, and 2017. The PSLE takes place after seven years of primary education, whereas the FTNA takes place after two years of secondary education. Thus, students taking the FTNA in 2015 are expected to have taken the PSLE in 2013 or before.

As the exam records do not contain a personal identification number, the names of the students in the FTNA are merged with the names of the students in the PSLE two years before. Students who have the

[2] Except for the exam in Kiswahili, exams are still conducted in English.

same names as other students in either the FTNA or the PSLE two years before are removed from the analysis. For students taking the PSLE, 2.0 per cent have a name duplicate within the year of taking the exam, whereas the same number for FTNA students is 1.6 per cent. Excluding students based on their names will not bias the results as long as parents giving common names to their children are indistinguishable from other parents.[3]

After excluding students with a name duplicate, the names of FTNA students are merged with the names of PSLE students of two years before. Of all FTNA students with no name duplicate in the FTNA nor in the PSLE, 51.6 per cent are uniquely identified in the PSLE. A falsification test is performed, in which FTNA students are merged with PSLE students from one year before. As students are not expected to complete two years of secondary schooling in one year, this exercise should result in substantially fewer uniquely merged students. Yet, despite having no name duplicate within a specific year, students may have name duplicates over time. Thus, there could be a low number of students being merged between the FTNA and the PSLE from one year before. In line with expectations, only 1.8 per cent of FTNA students without a name duplicate are uniquely merged with a PSLE student from the year before. The merging of names results in a panel dataset of approximately 635,000 students observed in two time periods. The next subsection on descriptive statistics discusses how the sample students differ from the total population of students, while a robustness analysis formally accounts for sample selection.

Information on school ownership is obtained by the President's Office, Regional Administration and Local Government (PO-RALG). School head teachers complete a form asking about ownership type and send it to the Ward Education Coordinator's office (WEC) for verification. Next, the WEC sends the information to the District Executive Director's office, where the information is entered into the Basic Education Information System. Finally, the PO-RALG processes the data and presents them to the public.

In addition to the exam records applied in the current paper, the National Panel Surveys from 2013 and 2015 are utilized to identify regions with relatively high and low consumption growth rates. This information is useful in a robustness analysis testing whether income growth is an important driver for the results.[4]

3.3 Descriptive statistics

Table 2 presents the descriptive statistics for the variables of interest to the current paper. Columns 1 and 2 present population means and standard deviations, respectively. The variables *GPA PSLE*, *GPA PSLE other*, and *Private primary* are based on exam records from 2,314,638 primary school students taking the PSLE in 2013, 2014, or 2015. The remaining variables are based on exam records from 1,246,267 secondary school students taking the FTNA in 2015, 2016, or 2017. Next, columns 3 and 4 present the means and standard deviations for the applied sample. All variables are based on the same 635,112 students. Finally, columns 5 and 6 split the applied sample into private secondary school students and public secondary school students. In addition to the descriptive statistics presented in Table 2, the regional distribution of the sample and the distribution of subject-specific grades can be seen in Table A1 and Figure A1 of Appendix A.

In all specifications tested, the dependent variable *GPA FTNA* refers to student achievement at the FTNA taking place after two years of secondary school. This achievement is defined as the grade point average

[3] While one could argue parents giving common names to their children are different from other parents, weighting students to get a representative sample does not change the results (see Section 6).

[4] Results are available in Appendix B.

Table 2: Descriptive statistics for all students and the applied sample

	Pop. mean	Pop. std.	Sample mean	Sample std.	Private mean	Public mean
GPA FTNA	1.308	0.881	1.318	0.886	2.407	1.198
GPA PSLE	1.664	0.832	2.229	0.696	2.758	2.170
GPA PSLE other	1.713	0.780	2.229	0.605	2.434	2.206
Private primary	0.034	0.180	0.065	0.247	0.455	0.022
Private secondary	0.182	0.386	0.099	0.299	1.000	0.000
Female	0.516	0.500	0.524	0.499	0.549	0.521
Secondary school size	146	95	148	94	122	151
Peers PSLE	2.224	0.426	2.225	0.417	2.756	2.167
Cohort 2016	0.325	0.468	0.312	0.463	0.324	0.311
Cohort 2017	0.388	0.487	0.410	0.492	0.367	0.415
Religious courses	0.282	0.450	0.264	0.441	0.422	0.247
Bible course	0.085	0.279	0.070	0.255	0.319	0.042
Islam course	0.230	0.421	0.228	0.420	0.120	0.240
Girls only secondary	0.034	0.182	0.031	0.173	0.203	0.012
Boys only secondary	0.017	0.130	0.016	0.125	0.083	0.008
N	See notes		635,112		63,172	571,940

Notes: 'Pop. mean' refers to the population mean. Population means of *GPA PSLE*, *GPA PSLE other*, and *Private primary* are based on 2,314,638 primary school students. The population means of the remaining variables are based on 1,246,267 secondary school students. 'Pop. std.' refers to the standard deviation of all students. Sample mean refers to the applied sample. The last two columns provide mean values for sample students attending private and public secondary schools, separately. Regional distribution of the sample and distribution of subject-specific grades can be seen in Table A1 and Figure A1, respectively, of Appendix A. *Religious courses* is an indicator for whether the student's secondary school provides elective courses in either Bible knowledge or Islamic knowledge.

Source: author's calculations.

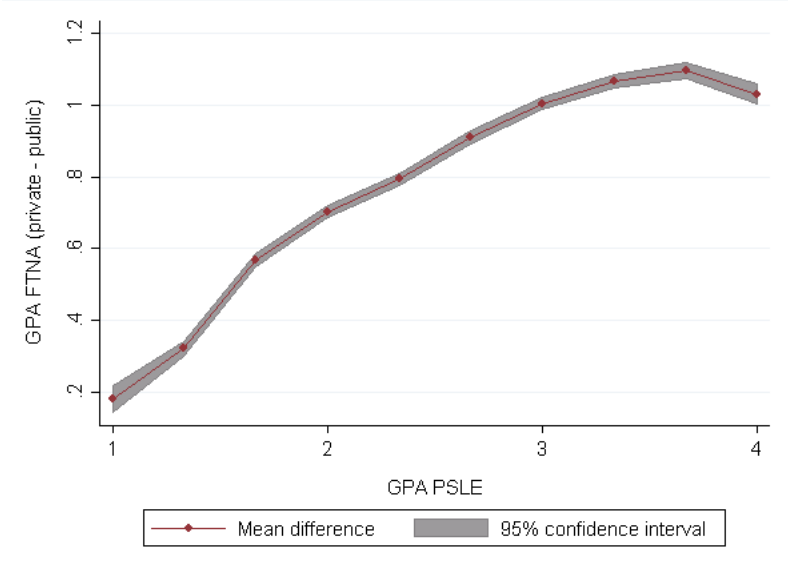
(GPA) based on exam scores in Kiswahili, English, and mathematics.[5] This approach is taken as these core subjects are the only subjects that can be directly linked between primary and secondary school. Grade 'A' is given four points, 'B' is given three points, 'C' is given two points, 'D' is given one point, and 'F' is given zero points.[6] The average GPA in the core subjects in secondary school is similar for the applied sample and the full population of students taking the FTNA. It is further noticed that private school students perform substantially better in the core subjects in secondary school. Conditional on lagged achievement, Figure 1 illustrates how both low-achieving and high-achieving students perform better in private schools compared to public schools. The difference, however, is substantially larger for students performing better in primary school.

GPA PSLE is calculated the same way as *GPA FTNA*. Thus, only Kiswahili, English, and mathematics are used for the GPA calculation. The GPA is found to be larger for the applied sample compared to the full population of primary school students. The reason is that the applied sample includes only students progressing to secondary school, whereas the full population of primary school students also includes students not progressing to secondary school. Consequently, the applied sample is not considered to be representative for the entire primary school student population. The gap in *GPA PSLE* between public and private secondary school students suggests private schools attract better students. The variable *GPA PSLE other* measures the primary school GPA based on the subjects community knowledge and science. Similar to *GPA PSLE*, the applied sample has a higher average of *GPA PSLE other* than the full population of primary school students, and private school students tend to perform better than public

[5] The official GPA is calculated by taking the average of the seven highest graded subjects for a student (Government of Tanzania, 2015).

[6] In secondary school in 2015, there is also the possibility of getting 'B+' and 'E'. 'B+' is given the same points as a 'B', while 'E' corresponds to zero points. For more on the grading system, see Government of Tanzania (2015).

Figure 1: Difference in average GPA for private and public school students conditional on lagged achievement



Notes: The y-axis refers to the difference in average GPA of English, Kiswahili, and mathematics in secondary school between private school students and public school students. *GPA PSLE* is the average of primary school exam scores in English, Kiswahili, and mathematics. The figure is based on 633,481 sample students. Students with a GPA PSLE below 1 are excluded due to large confidence bounds caused by few observations.

Source: author's calculations.

school students. In the empirical analysis, variables related to exam scores are standardized by the sample means and sample standard deviations for simpler comparison to other studies.

The main explanatory variable applied in the current paper is the private secondary school dummy taking the value 1 if a student was enrolled in a private secondary school when taking the FTNA. Around 10 per cent of the sample students attend a private secondary school, meaning there is an under-representation of private secondary school students. In the robustness section, two approaches are pursued to test whether the private school learning premium suffers from selection bias: (1) estimating a Heckman selection model; and (2) estimating a model using sample weights to get a representative sample in regard to student ability, gender, private schooling, year of exam, ability of peers, and school size. Over time, 33,589 students switch from public to private school, while 12,310 students switch from private to public school. A total of 546,860 students are always in public school, while 28,098 students are always in private school.[7]

Additional variables in the dataset include secondary school size, peer effects, gender of the student, and the cohort the student belongs to. The size of the secondary school is measured as the number of students taking the FTNA, and it is noticed that public secondary schools tend to be larger than private secondary schools. To proxy for peer effects, *Peers PSLE* takes the average primary school GPA of a student's schoolmates in secondary school. By using the primary school GPA instead of secondary school GPA, we make sure the peer effects do not capture the effect from the private school learning premium.

In terms of school heterogeneity, 26 per cent of the applied sample attends a secondary school offering elective courses in either Bible knowledge or Islamic knowledge. In particular, schools offering Bible knowledge are popular among private secondary schools, while schools offering Islamic knowledge are more prevalent in the public sector. Same-gender secondary schools are far more common in the private school sector and to a large extent are driven by schools for girls.

[7] For 14,255 students, the type of primary school could not be determined.

4 Methodology

Six main specifications are estimated in the current paper, including the standard value-added model and a flexible value-added model derived in Section 2. The first five specifications are included to illustrate different sources of bias, whereas the sixth model specified is the preferred flexible value-added model. In all specifications, standard errors are corrected for within secondary school correlation.

The specifications presented do not include family-supplied inputs, which could potentially be an issue for identification. If, however, lagged student achievement and peer effects are accounted for, controlling for socio-economic variables is found to have a very limited and insignificant impact on school value-added estimates (Andrabi et al., 2011; Deming et al., 2014; Elks, 2016; Muralidharan and Sundararaman, 2015) and teacher value-added estimates (Aaronson et al., 2007; Ballou et al., 2004; Chetty et al., 2014; Kane and Staiger, 2008). As the preferred model accounts for lagged achievement in the *same* primary school in the *same* cohort, the potential concern is mitigated even further. Angrist et al. (2017) formally test the performance of value-added models in comparison to experimental models. While they find value-added models to be biased, the effect is modest; regressing school effects from an experimental model against school effects from a value-added model yields a coefficient estimate of 0.86, which should have been 1 if there was no bias. The difference is statistically significant only at the 10 per cent level. In a robustness analysis, sensitivity towards unobserved heterogeneity is further examined.

The first model applied is the simple cross-sectional OLS model given by Equation 8:

$$GPA_{i,s,c} = \beta_0 + \beta_1 Private_s + \beta_2 Female_i + \beta_3 Size_s + \delta_c + \varepsilon_{i,s,c}. \tag{8}$$

Subscripts i, s, and c represent students, secondary schools, and cohorts, respectively. The sample consists of student cohorts taking the FTNA in 2015, 2016, or 2017. The parameter of main interest is β_1, measuring the private school learning premium. This model provides unbiased coefficient estimates if the error term is uncorrelated with the explanatory variables. This is likely not true, however, as students in private secondary schools tend to outperform public secondary school students before they start secondary school.

One may account for private school students being academically stronger students by including GPA from the PSLE as an explanatory variable. Including this variable gives the following standard value-added model:

$$GPA_{i,s,p,c} = \beta_0 + \beta_1 Private_s + \beta_2 Female_i + \beta_3 Size_s + \beta_4 GPA_{i,p} + \delta_c + \varepsilon_{i,s,p,c}. \tag{9}$$

Subscript p represents primary schools, meaning $GPA_{i,p}$ is primary school GPA for individual i. This variable is also called the persistence parameter as it measures how well exam scores from the previous time period explain exam scores in the current time period. Again, for this model to provide unbiased coefficient estimates, the error term has to be uncorrelated with the explanatory variables.

Better primary schools, however, may have taught students other things than what is needed for the PSLE. For instance, by focusing more on English to make the students understand the teaching in secondary school or preparing them for what is expected at the new level of study. Given such unobserved primary school heterogeneity exists and private school students attend better primary schools, the private school learning premium is biased upward in the model specified in Equation 9. Consequently, a model including primary school fixed effects is proposed in Equation 10:

$$GPA_{i,s,p,c} = \beta_0 + \beta_1 Private_s + \beta_2 Female_i + \beta_3 Size_s + \beta_4 GPA_{i,p} + \delta_c + \delta_p + \varepsilon_{i,s,t}. \tag{10}$$

The abilities of the student's new classmates in secondary school, however, are likely correlated with whether or not the student attends a private or public secondary school. At the same time, it is well-established in the literature that peer effects exist (Epple and Romano, 2011; Sacerdote, 2011). Thus, in order to disentangle the true private school learning premium from peer effects, one needs to account for the latter.

Peer effects can be accounted for by including an explanatory variable measuring the average PSLE exam score for a student's schoolmates in secondary school. While the performance of schoolmates is generally highly correlated with individual performance, Angrist (2014) finds causal peer effects to be less satisfactorily explored. The author argues the most compelling results are found when manipulating peer characteristics in a way that is unrelated to the characteristics of the individual student, but it is also in these cases the literature is least likely to find peer effects. Manski (1993) stresses three problems with standard approaches to measuring peer effects: (1) students self-select into specific groups; (2) students could simultaneously affect each other; and (3) peer effects may arise due to students' background characteristics or students' behaviour, and it is difficult to distinguish between these two effects. While *lagged* achievement of current peers addresses the second issue of simultaneity, it could very well be that students with higher ambitions self-select into the same secondary schools.[8] Higher ambitions, however, will to some extent be captured by the lagged student achievement.[9] The model accounting for peer effects is given by Equation 11:

$$\begin{aligned} GPA_{i,s,p,c} =& \beta_0 + \beta_1 Private_s + \beta_2 Female_i + \beta_3 Size_s + \beta_4 GPA_{i,p} + \beta_5 Peer\ effect_{i,s,c} \\ & + \delta_c + \delta_p + \varepsilon_{i,s,p,c}, \end{aligned} \tag{11}$$

where *Peer effect*$_{i,s,c}$ is the average PSLE score for student i's schoolmates in secondary school s.[10] The applied formula for calculating peer effects is given by Equation 12, where j is student i's schoolmates in secondary school s:

$$Peer\ effect_{i,s,c} = \frac{\sum_{j \neq i} GPA_{j,p}}{Size_s - 1} \tag{12}$$

One critique of the model specified in Equation 11 could be that students have different returns to school inputs, such as high-ability students benefiting more from a given level of school inputs. Consequently, a 'primary school, lagged achievement, and cohort' fixed effect model is proposed. That is, students are compared to other students from the same primary school achieving the same GPA in the same year. Thus, students with the same school inputs who have benefited similarly from these inputs after seven years of primary school are compared. This approach is feasible only due to the unique data applied in the current paper as the approach requires a student time panel, achievement information on previous schoolmates, lagged achievement information on current schoolmates, and switchers between public and private schools. The specification for the primary school, lagged achievement, and cohort fixed effect model is presented in Equation 13:

$$GPA_{i,s,p,g,c} = \beta_0 + \beta_1 Private_s + \beta_2 Female_i + \beta_3 Size_s + \beta_4 Peer\ effect_{i,s,c} + \delta_{p,g,c} + \varepsilon_{i,s,p,g,c}. \tag{13}$$

Subscript g represents primary school GPA. With 17,412 primary schools, three cohorts of students, and 13 primary school GPA possibilities, this model allows for 679,068 dummy variables. Of these dummies, 482,746 are omitted due to missing observations as some schools have no students getting a specific GPA in a specific year. This model assumes students from the same primary school with

[8] Further manipulating the peer effect variable to only include current peers from another primary school does not change the results.

[9] Since the peer effects variable also acts as a control variable to capture socio-economic characteristics, the current paper refrains from claiming a causal effect from peer effects to achievement.

[10] It could be that private schools are better at capitalizing on peer effects. Following this hypothesis, the peer effects variable is interacted with the private school dummy in Appendix B.

the same primary school GPA in the same year would continue to perform similarly after two years of secondary school if they were placed in the same secondary school.

While estimating the model specified in Equation 13 would be a significant methodological contribution in itself, there is another issue often overlooked in the literature. In the lagged value-added model, it is assumed the effect from unobserved ability like learning speed decays at the same rate as inputs to the cumulative learning process. A violation of this assumption could lead to the private school learning premium being biased if unobserved ability is correlated with both exam scores and private school enrolment. The direction of the bias is ambiguous. Despite comparing students from the same primary school getting the same GPA based on Kiswahili, English, and mathematics after seven years of primary schooling, there could be differences in unobserved ability. Students with higher learning speed are expected to perform better in the two remaining exams in primary school. Thus, as a proxy for unobserved ability, the exam scores in community knowledge and science from the PSLE are used. The preferred specification to the current paper is given by Equation 14:

$$\begin{aligned} GPA_{i,s,p,g,c} =& \beta_0 + \beta_1 Private_s + \beta_2 Female_i + \beta_3 Size_s + \beta_4 Peer\ effect_{i,s,c} \\ &+ \beta_5 GPA\ other_{i,p} + \delta_{p,g,c} + \varepsilon_{i,s,p,g,c}, \end{aligned} \tag{14}$$

where $GPA\ other_{i,p}$ is the average exam score of community knowledge and science from the PSLE for student i.

A final issue often overlooked is measurement errors, which is found to be of significant importance in the value-added literature (Andrabi et al., 2011; Koedel et al., 2015; Lockwood and McCaffrey, 2014). Not accounting for measurement errors will result in a downward bias on the persistence parameter. The rationale is that most often students perform according to their true ability at exams. Sometimes, however, random measurement errors like sickness on the exam day or unlucky exam questions for the individual affect students' exam scores. Thus, when these measurement errors are in effect, the relationship between exam scores over time is dampened, leading to a bias towards zero for the persistence parameter. This bias in the persistence parameter may also contaminate the private school learning premium if enrolment in private secondary school is correlated with achievement at the PSLE after conditioning on the other explanatory variables. The direction of the bias is positive (negative) if there is a positive (negative) correlation between the two variables. As will be evident from a subject-specific robustness analysis, accounting for measurement error does not change the private school learning premium in any major way, suggesting a low conditional correlation between lagged achievement and enrolment into private secondary school. Furthermore, measurement errors are predominantly a problem when studying specific exam scores. When studying an overall GPA, correlated measurement errors across subjects are required to constitute a problem (Andrabi et al., 2011). The exam scores used as a proxy for unobserved ability could also mitigate any potentially correlated measurement errors across the three core subjects.

5 Results

The results from estimating the models specified in Equations 8–14 are presented in Table 3. The model of main interest is presented in column (6), whereas columns (1)–(5) are included to illustrate how different sources of bias influence the private school coefficient estimate.

The model in column (1) accounts for student gender, the year of taking the FTNA, and school size. The coefficient representing the private school learning premium suggests that attending a private secondary school instead of a public secondary school increases a student's GPA in Kiswahili, English, and mathematics by 1.40 standard deviations after two years. Descriptive statistics in Section 3, however,

Table 3: Results from estimating the main specifications

Dependent variable: GPA_s $(FTNA)$	(1)	(2)	(3)	(4)	(5)	(6)
$Private_s$	1.396***	0.997***	0.631***	0.530***	0.431***	0.450***
	(0.038)	(0.025)	(0.019)	(0.018)	(0.014)	(0.014)
$log(School\ size_s)$	0.095***	0.022**	–0.091***	–0.113***	–0.081***	–0.084***
	(0.012)	(0.009)	(0.009)	(0.008)	(0.007)	(0.007)
$Female$	–0.161***	–0.100***	–0.061***	–0.065***	–0.010**	0.057***
	(0.011)	(0.007)	(0.005)	(0.005)	(0.005)	(0.005)
$Cohort16$	–0.095***	–0.120***	–0.112***	–0.124***		
	(0.006)	(0.006)	(0.006)	(0.006)		
$Cohort17$	0.102***	–0.001	0.017**	–0.025***		
	(0.008)	(0.008)	(0.007)	(0.008)		
GPA_p $(PSLE)$		0.446***	0.548***	0.512***		
		(0.008)	(0.006)	(0.004)		
$Peer\ effects_s$				0.122***	0.178***	0.153***
				(0.008)	(0.005)	(0.005)
$GPA\ other_p$ $(PSLE)$						0.223***
						(0.002)
$Constant$	–0.524***	–0.114***	0.434***	0.573***	0.352***	0.328***
	(0.054)	(0.042)	(0.041)	(0.037)	(0.035)	(0.035)
Primary school fixed effects	No	No	Yes	Yes	No	No
'*Primary school* × *Primary school GPA* × *Cohort*' fixed effects	No	No	No	No	Yes	Yes
N	635,112	635,112	635,112	635,112	635,112	635,112
R^2	0.185	0.365	0.515	0.52	0.725	0.739

Notes: Column (6) acts as the preferred model, while the former five columns are included to illustrate different sources of bias. GPA_s and GPA_p are the GPA of the subjects Kiswahili, English, and mathematics in secondary and primary school, respectively. $Peer\ effects_s$ is the average GPA of the subjects Kiswahili, English, and mathematics in primary school for secondary school schoolmates. $GPA\ other_p$ is the GPA of the subjects community knowledge and science in primary school. GPA_s, GPA_p, $Peer\ effects_s$, and $GPA\ other_p$ are standardized by their sample means and standard deviations. Standard errors are clustered at the secondary school level. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Source: author's calculations.

demonstrated private secondary school students were already performing better than public secondary school students at the PSLE. Thus, the private school learning premium estimated in column (1) is highly susceptible to omitted variable bias.

From column (2) it is noticed that the coefficient estimate associated with private secondary schooling drops by around 29 per cent when including lagged achievement. This is the phenomenon of 'cream skimming', demonstrating private schools attracting better students. The coefficient associated with GPA from the PSLE, also called the persistence parameter, is obviously highly significant. A one standard deviation increase in the PSLE exam scores is associated with an increase in the FTNA exam scores of 0.45 of a standard deviation. The private school learning premium could be upwardly biased in column (2) if private school students went to better primary schools. The intuition is that good primary schools teach their students things that are useful in secondary school, but they cannot be perfectly captured by the exam scores in primary school. The private school coefficient estimate drops by around 37 per cent after including primary school fixed effects, highlighting the importance of comparing students from the same primary school.

Another potential issue is peer effects. If well-performing students end up in the same secondary schools, and the ability of schoolmates influences a student's FTNA exam scores, the private school coefficient estimate is still positively biased. The model in column (4) accounts for peer effects by including the average PSLE score for a student's secondary school schoolmates. The estimated private school learning premium is reduced to 0.53 of a standard deviation, and peer effects are highly positive and significant. The drop in the private school learning premium of 16 per cent after including peer effects tells a story of two mechanisms at play causing private school students to perform better: (1) students attending private schools have high-ability peers, potentially resulting in positive spillover effects;[11] and (2) a true private school learning premium, which could be caused by a number of different factors, such as efficient management, more focus on student achievement, and better facilities, among others.

In Section 2 describing the theoretical framework, it is argued that students could have different returns to school inputs dependent on their ability. By including a '*primary school* × *primary school GPA* × *cohort*' fixed effect, these different returns can be taken into account as students are compared to other students from the same primary school achieving the same primary school GPA. These students are likely to have received the same school-supplied inputs and benefited similarly from these. Column (5) presents the results from this approach. While the coefficient estimate associated with the private school learning premium has declined further compared to the first four models, 0.43 of a standard deviation is still considered a large learning premium after two years of secondary schooling.

Finally, the model estimated in column (6) of Table 3 further includes GPA based on the subjects community knowledge and science from primary school. Section 4 argued any significant effect from this additional explanatory variable could be due to unobserved ability or correlated measurement errors. A third option is complementarities between subjects. For instance, if a student is good at science, it may become easier to learn mathematics in secondary school. The coefficient associated with $GPA\ other_p$ is highly significant, suggesting that students performing better in community knowledge and science in primary school also perform better in the core subjects in secondary school despite accounting for lagged achievement in core subjects. Noteworthy is that the private school learning premium increases slightly, which is indicative of students not selecting into private school based on unobserved ability. This result is in line with Singh's (2015) finding that students in India select into private schools based on socio-economic characteristics rather than unobserved ability. The preferred coefficient estimate suggests that attending private secondary school is on average expected to improve a student's FTNA GPA in Kiswahili, English, and mathematics by 0.45 standard deviations after two years of secondary schooling.

The preferred result in column (6) is similar to the private school learning premium estimated by Andrabi et al. (2011) using data from Pakistan. They show, however, that the private school learning premium is mostly driven by an effect in the first year of private schooling. A robustness test in Appendix B suggests a higher learning premium in the first year could also be the case for Tanzanian secondary school students.

6 Robustness analyses

The following robustness analyses elucidate different threats to identification and types of heterogeneity. These threats to identification include endogeneity of the private school learning premium and sample selection. In terms of heterogeneity, a subject-specific analysis is performed, and sensitivity to unobserved heterogeneity is tested. The methodology and results of each robustness analysis are commented upon, while the results themselves are presented in Appendix A. In Appendix B, the private secondary school enrolment dummy is interacted with different geographical areas, peer effects, a religious school dummy, a same-gender school dummy, and year of taking the FTNA.

[11] It is important to stress that the peer effects variable could be endogenous even after controlling for lagged achievement. This is because peer effects and lagged achievement, according to the literature, capture the effects from family-supplied inputs.

6.1 Endogeneity of private school learning premium

Despite including lots of controls that could influence both achievement and private school enrolment, the preferred model in Section 5 does not formally account for selection into private schools. Consequently, the estimated private school learning premium could still be endogenous given it is a specific type of student enrolling in private secondary school. Table A2 compares the results from an IV model with the preferred value-added model. Whether a student fails the primary school exams is used as an instrument for enrolment into private secondary school. Students failing primary school are not eligible to enter a public secondary school, which leads to a substantially larger share of students entering private secondary school. As illustrated in Figure A2, since a pass/fail covers more subjects than the core subjects (Kiswahili, English, and mathematics), it follows that for many given outcomes on the core subjects we observe some students who pass and some who fail.

The relevance of this instrument is supported by the Cragg–Donald Wald F statistic in column (2). In regard to validity, students failing the primary school exams tend to end up in the same secondary schools. Agglomeration of failing students could create a learning environment where failing becomes more acceptable. If this agglomeration of failing students is not accounted for, one could argue the instrument is not valid as failing the primary school exams will have a negative effect on secondary school exams through the agglomeration of failing students. Thus, to counter the above-mentioned issue, the preferred model is extended with a control variable measuring the share of secondary school peers who failed the primary school exams. While one cannot explicitly test the validity of the instrument, including the instrument in the value-added model yields an insignificant coefficient estimate for the instrument.[12]

The private school learning premium in column (1) increases slightly by including the share of secondary school peers who failed the primary school exams. In line with expectations, the share of secondary school peers failing primary school has a negative effect on performance at the FTNA. In column (2) the private school learning premium remains close to the value-added estimate. Following these results, attending private school is argued to have a positive causal effect on secondary school exam scores.

6.2 Sample selection and representativeness

The descriptive statistics in Section 3 illustrated how the sample at hand differs from the total population of students. Naturally, this makes one wonder whether the estimated private school learning premium is representative to the entire student population. To counter this selection issue, two approaches are pursued. First, following Heckman (1979), a sample selection model is estimated. Second, sample weights are computed and applied to the preferred model.

The sample selection model estimates in a first-stage probit model the probability of being part of the sample. The first-stage probit model can be summarized by Equation 15:

$$Pr(Sample_i = 1|X_1) = \Phi(X_1\beta_1), \tag{15}$$

where $Sample_i$ indicates whether student i is in the sample. The explanatory variables in X_1 must be available for all secondary school students. The exclusion restriction relies on the length of student names. Both students with relatively short and long names are less likely to be in the sample. Students with short names are more likely to have a name duplicate and therefore be excluded from the sample. Students with long names have higher probability of misspelling and therefore not being merged with

[12]Results are available upon request.

their primary school exam records. Consequently, both the linear and the quadratic term of name length are included in the first-stage probit model. Both terms are found to be highly significant.[13] Next, based on linear predictions of the first-stage model, the inverse Mill's ratio is calculated.

The results from including the inverse Mill's ratio into the preferred model can be seen in Table A3, column (1). The inverse Mill's ratio is insignificant, suggesting sample selection is not a major issue for the preferred model. As the inverse Mill's ratio is very insignificant, the coefficient estimates on the variables in the model remain identical to the coefficient estimates in the preferred model.

To counter non-representativeness, sample weights are calculated to give representative estimates in regard to student ability, gender, year of exam, ability of peers, and school size. The first-stage probit model from the Heckman sample selection model is used to calculate the probability of a student being in the sample. Next, the inverse of the probability of being in the sample is used as sample weights in the preferred model. The results from including these sample weights are presented in Table A3, column (2). There is a marginal drop in the private school learning premium compared to the preferred model, and the change is insignificantly different from zero.

6.3 Sensitivity to unobserved heterogeneity

Oster (2017) proposes a method to examine what happens to a specific coefficient estimate assuming one is able to explain all variation in the dependent variable, and selection on observables is informative about selection on unobservables. The idea is that the difference between the coefficient estimates of the explanatory variable of interest from an uncontrolled model and the preferred model is informative about what would happen to the coefficient estimate should we account for unobserved controls.

In the restricted estimator case, it is assumed that selection on unobservables is equal to selection on observables. It is further assumed that the coefficient estimate to the explanatory variable of interest is independent of controlling for the true effects from the observed control variables. That is, including an index equal to the observed control variables multiplied by their coefficient estimates from a regression where unobserved heterogeneity is also controlled for. Under these conditions, the following β^* is a consistent estimator of true β:

$$\beta^* = \widetilde{\beta} - \left(\mathring{\beta} - \widetilde{\beta}\right) \frac{R^2_{\max} - \widetilde{R^2}}{\widetilde{R^2} - \mathring{R}^2}, \tag{16}$$

where $\widetilde{\beta}$ is the coefficient estimate of the private school dummy in the preferred model, $\mathring{\beta}$ is the coefficient estimate of the private school dummy in the uncontrolled model, $R^2_{\max}$ is the R^2 from a hypothetical model accounting for unobserved controls, $\widetilde{R^2}$ is the R^2 from the preferred model, and $\mathring{R}^2$ is the R^2 from the uncontrolled model. Based on a sample of randomized results from top journal articles, it is suggested that $R^2_{\max} = 1.3\widetilde{R^2}$. This level of $R^2_{\max}$ ensures that 90 per cent of the randomized results survive the sensitivity test. The reason for this adjustment is that the outcome variable in most empirical settings cannot be perfectly explained due to, for example, measurement errors.

Following the method laid out above, the private school learning premium in the current paper is robust to unobserved controls, but the magnitude of the coefficient drops from 0.40 to 0.09.[14] In a sample of

[13]Results are available upon request.

[14]In the case of the unrestricted estimator, the preferred private school learning premium does *not* survive the sensitivity test. The relative degree of selection on unobservables compared to selection on observables has to be less than 0.40 in order for the private school learning premium to be positive.

non-randomized results from top journal articles, only 45 per cent survive the proposed sensitivity test without changing sign (Oster, 2017).

Since variables such as peer effects, lagged exam scores, and primary school are highly correlated with both a student's current exam score and private school enrolment, including them as control variables leads to a lower estimated private school learning premium. Assuming unobservable controls are similarly correlated with private school enrolment, and have the same explanatory power, seems unrealistic. The author of the proposed sensitivity test further argues that setting the relative degree of selection on unobservables equal to selection on observables may serve as an upper bound. In a wage data simulation exercise, the author finds an average relative degree of selection on unobservables equal to 0.545 of the selection on observables. Obviously, this value depends on the importance of the omitted control variables. The relative degree of selection can also take negative values if there are other variables like $GPA\ other_p$ having a positive impact on GPA_s and a negative conditional correlation with private secondary schooling.

6.4 Subject-specific private school learning premiums

Table A4 seeks to shed light on whether it is a specific subject that is driving the overall private school learning premium. To study these subject-specific private school learning premiums, the GPA from Kiswahili, English, and mathematics is replaced by the exam scores in each subject. Columns (1), (3), and (5) apply the standard lagged value-added model for the subjects Kiswahili, English, and mathematics, respectively. As previously discussed, this analysis is likely to suffer from measurement error. Consequently, the analysis follows Andrabi et al. (2011) by instrumenting lagged achievement in a specific subject with lagged achievement in other subjects. Columns (2), (4), and (6) apply this IV method for exam scores in Kiswahili, English, and mathematics, respectively. In order to compare students benefiting similarly from the same school inputs, the last three columns of Table A4 include a *primary school* $\times$ *instrumented subject-specific exam score* $\times$ *cohort* fixed effect. Based on exam scores in other subjects, the exam score in the subject of interest is predicted. Next, students with similarly predicted subject-specific exam scores from the same primary school in the same cohort are compared by including the aforementioned fixed effect.[15]

The first six columns demonstrate that: (1) the private school learning premiums are significantly positive for all three subjects; (2) in line with theory, accounting for measurement error increases the persistence parameter; and (3) the private school learning premiums change only slightly when accounting for measurement error, indicating a weak conditional correlation between lagged achievement and private secondary school enrolment. Turning to the flexible value-added models in columns (7)–(9), the private school learning premiums decrease, which is in line with the main results in Section 5. Attending private secondary school is associated with increases in Kiswahili, English, and mathematics FTNA exam scores of 0.28, 0.39, and 0.50 standard deviations, respectively. Thus, private schools improve students' exam scores in all three subjects.[16]

[15]Predicted subject-specific exam scores are split by each 0.1 point (for example, students getting a predicted exam score of 1.30 to 1.39 are compared).

[16]Several other subjects are taught in secondary school. Kiswahili, English, and mathematics, however, are the only ones with a clear link between primary school and secondary school.

7 Conclusion

The literature on the private school learning premium in developing countries is mostly focused around South Asia, while evidence from sub-Saharan African countries is lacking. Most studies apply simple cross-sectional data sources, leaving only a minority of studies applying value-added models. The value-added models applied in the literature generally have to impose strong assumptions to achieve identification, and they rely on data sources with a low number of switchers between public and private schools.

The current paper seeks to improve the existing literature in four dimensions: (1) estimating a flexible value-added model relaxing three out of four commonly imposed assumptions in standard value-added models; (2) providing evidence for a geographical area with relatively little existing evidence; (3) estimating an instrumental variable model to determine causality; and (4) examining subject-specific private school learning premiums.

The identification strategy applied is, to the best of the author's knowledge, unseen in the literature on estimating the private school learning premium. Compared to other value-added models, the identification strategy provides a credible estimate of the learning premium as students are compared to their primary school schoolmates receiving the same primary school GPA in the same year. The proposed method, however, has heavy requirements for the applied data as one must have information on student lagged and current achievement, current schoolmates' lagged achievement, previous schoolmates' lagged and current achievement, and previous schoolmates' current school enrolment. Tanzanian exam records fulfil these requirements. The current paper applies a sample of 635,112 secondary school students, of which 33,589 students switch from public to private schooling, and 12,310 students switch from private to public schooling.

The preferred result on the private school learning premium suggests that attending private secondary school is expected to increase the FTNA exam scores by 0.45 of a standard deviation after two years of secondary schooling. In line with expectations, a standard value-added model and an OLS model bias the private school learning premium substantially upward. An IV model confirms the private school learning premium is causal, and a Heckman selection model demonstrates the preferred model is highly robust to sample selection. The robustness section showed positive subject-specific learning premiums of 0.28, 0.39, and 0.50 standard deviations for Kiswahili, English, and mathematics, respectively. Finally, although the coefficient estimate dropped considerably, the private school learning premium survived a harsh test for unobserved heterogeneity.

Further research is needed to determine the mechanisms through which private schools perform better in order to improve learning in public schools. It would also be of interest to acquire similar administrative data from other sub-Saharan African countries to study whether the large private school learning premium is unique to the Tanzanian context.

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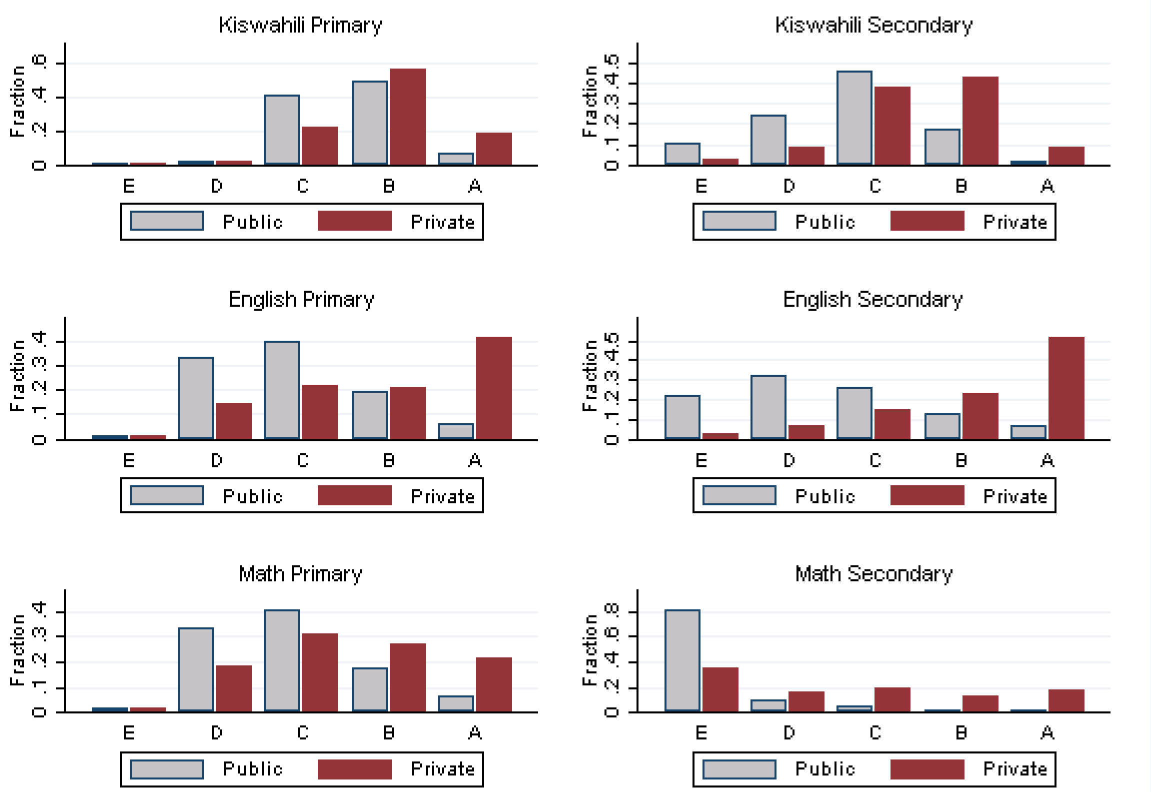
Appendix A: sample distributions and robustness analyses discussed in the main text

Table A1: Regional distribution of secondary school students in the sample

	Population	Sample	Private secondary	Public secondary
Arusha	0.056	0.051	0.072	0.049
Dar Es Salaam	0.106	0.098	0.168	0.091
Dodoma	0.035	0.037	0.036	0.037
Geita	0.032	0.038	0.009	0.041
Iringa	0.035	0.032	0.035	0.032
Kagera	0.048	0.044	0.032	0.045
Katavi	0.008	0.008	0.002	0.009
Kigoma	0.031	0.023	0.032	0.022
Kilimanjaro	0.071	0.072	0.130	0.066
Lindi	0.016	0.017	0.004	0.019
Manyara	0.027	0.023	0.012	0.025
Mara	0.043	0.048	0.018	0.051
Mbeya	0.075	0.083	0.083	0.083
Morogoro	0.050	0.045	0.053	0.044
Mtwara	0.027	0.031	0.012	0.033
Mwanza	0.077	0.081	0.064	0.083
Njombe	0.022	0.023	0.024	0.022
Pwani	0.034	0.035	0.078	0.031
Rukwa	0.016	0.013	0.007	0.014
Ruvuma	0.032	0.026	0.026	0.026
Shinyanga	0.029	0.034	0.022	0.035
Simiyu	0.023	0.030	0.005	0.033
Singida	0.023	0.023	0.013	0.024
Songwe	0.001	0.000	0.004	0.000
Tabora	0.028	0.027	0.024	0.027
Tanga	0.055	0.056	0.037	0.058
N	1,246,267	635,112	63,172	571,940

Source: author's calculations.

Figure A1: Distribution of subject-specific exam scores for the applied sample



Notes: The distinction between public and private school students are at the secondary school level. Thus, the figures illustrate the fractions of public secondary school students getting a specific grade in primary and secondary school for different subjects, and the fractions of private secondary school students getting a specific grade in primary and secondary school for different subjects.

Source: author's calculations.

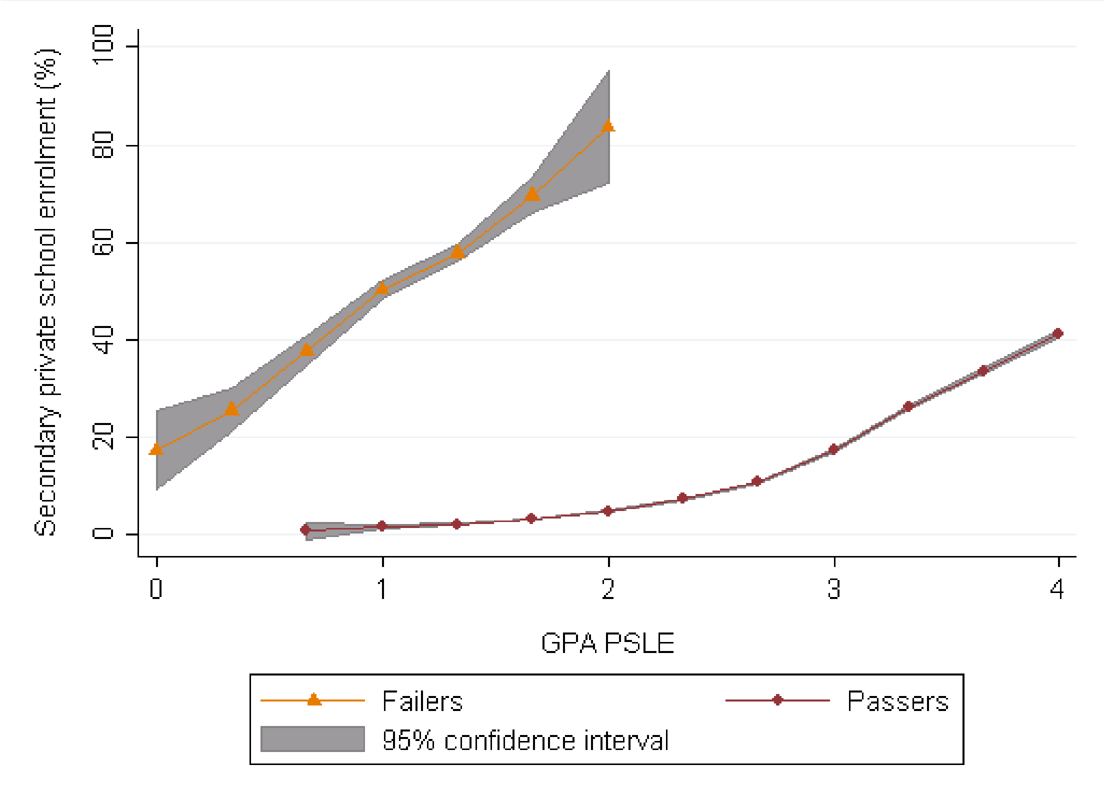
Table A2: Value-added model versus IV model

Dependent variable: GPA_s $(FTNA)$	Value-added (1)	IV (2)
$Private_s$	0.505***	0.535***
	(0.017)	(0.162)
log(School size$_s$)	–0.083***	–0.078***
	(0.007)	(0.027)
$Female$	0.058***	0.058***
	(0.005)	(0.005)
Peer effects$_s$	0.138***	0.132***
	(0.005)	(0.031)
GPA other$_p$ (PSLE)	0.223***	0.223***
	(0.002)	(0.002)
Failing peers$_s$	–0.523***	–0.603
	(0.057)	(0.430)
'*Primary school* × *Primary school GPA* × *Cohort*' fixed effects	Yes	Yes
Instrument: – *Failing PSLE*	No	Yes
Cragg–Donald Wald F statistic		771.2
N	635,112	635,112
R^2	0.739	0.739

Notes: The instrument, 'Failing PSLE' states whether a student failed the primary school exams. *Failing peers$_s$* is the share of secondary school peers failing the primary school exams. GPA_s is the GPA of the subjects Kiswahili, English, and mathematics in secondary school. *Peer effects$_s$* is the average GPA of the subjects Kiswahili, English, and mathematics in primary school for secondary school schoolmates. *GPA other$_p$* is the GPA of the subjects community knowledge and science in primary school. GPA_s, *Peer effects$_s$*, and *GPA other$_p$* are standardized by their sample means and standard deviations. Standard errors are clustered at the secondary school level. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Source: Author's own calculations.

Figure A2: Secondary private school enrolment for PSLE passers and failers



Notes: *GPA PSLE* is the average of primary school exam scores in English, Kiswahili, and mathematics. The figure is based on the main sample of 635,112 secondary school students.

Table A3: Sample selection and weighting

Dependent variable: $GPA_s\ (FTNA)$	(1)	(2)
$Private_s$	0.450***	0.447***
	(0.014)	(0.014)
log(School size$_s$)	–0.084***	–0.080***
	(0.007)	(0.007)
$Female$	0.057***	0.064***
	(0.005)	(0.005)
Peer effects$_s$	0.154***	0.152***
	(0.005)	(0.005)
GPA other$_p$ (PSLE)	0.223***	0.224***
	(0.002)	(0.002)
$Constant$	0.337***	0.086**
	(0.037)	(0.041)
Inverse Mill's ratio, λ_1	–0.013	
	(0.017)	
'*Primary school $\times$ Primary school GPA $\times$ Cohort*' fixed effects	Yes	Yes
N	635,112	635,112
R^2	0.739	0.868

Notes: in column (1), λ_1 origins from a first-stage probit model explain whether a student's PSLE records have been identified. This first-stage probit model is dependent on student ability, gender, cohort, length of student name, ability of peers, school size, whether the student has repeated a grade, and district fixed effects. In column (2), sample weights are applied to get a representative sample in regard to the same variables as in the first-stage probit model. GPA_s is the GPA of the subjects Kiswahili, English, and mathematics in secondary school. *Peer effects$_s$* is the average GPA of the subjects Kiswahili, English, and mathematics in primary school for secondary school schoolmates. *GPA other$_p$* is the GPA of the subjects community knowledge and science in primary school. GPA_s, *Peer effects$_s$*, and *GPA other$_p$* are standardized by their sample means and standard deviations. Standard errors are clustered at the secondary school level. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Source: author's calculations.

Table A4: Analysis of subject-specific exam scores (continued on next page)

Dependent variable:	Kiswahili FTNA score (1)	Kiswahili FTNA score (2)	English FTNA score (3)	English FTNA score (4)	Math FTNA score (5)	Math FTNA score (6)
$Private_s$	0.356***	0.314***	0.457***	0.478***	0.577***	0.580***
	(0.014)	(0.013)	(0.021)	(0.017)	(0.023)	(0.022)
PSLE score	0.317***	0.399***	0.330***	0.427***	0.401***	0.434***
	(0.002)	(0.003)	(0.004)	(0.003)	(0.005)	(0.005)
log(School size$_s$)	–0.072***	–0.084***	–0.080***	–0.084***	–0.102***	–0.106***
	(0.008)	(0.008)	(0.008)	(0.007)	(0.010)	(0.009)
$Female$	0.055***	0.074***	–0.110***	–0.087***	–0.154***	–0.089***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Peer effects$_s$	0.103***	0.060***	0.119***	0.063***	0.185***	0.183***
	(0.007)	(0.005)	(0.009)	(0.007)	(0.011)	(0.010)
$Cohort16$	0.051***	0.075***	–0.305***	–0.324***	0.014***	–0.029***
	(0.010)	(0.010)	(0.007)	(0.006)	(0.006)	(0.005)
$Cohort17$	0.050***	0.017	–0.140***	–0.203***	0.131***	0.027***
	(0.011)	(0.011)	(0.007)	(0.007)	(0.009)	(0.009)
$Constant$	0.243***	0.301***	0.549***	0.584***	0.456***	0.494***
	(0.039)	(0.037)	(0.038)	(0.034)	(0.047)	(0.045)
PSLE score instrumented	No	Yes	No	Yes	No	Yes
‘*Primary school* × *PSLE score* × *Cohort*’ fixed effects	No	No	No	No	No	No
Primary school fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
N	635,112	635,112	635,112	635,112	635,112	635,112
R^2	0.275	0.289	0.423	0.48	0.443	0.439

Analysis of subject-specific exam scores (continued from previous page)

Dependent variable:	Kiswahili FTNA score (7)	English FTNA score (8)	Math FTNA score (9)
$Private_s$	0.278***	0.387***	0.503***
	(0.014)	(0.016)	(0.022)
log(School size$_s$)	–0.074***	–0.056***	–0.080***
	(0.010)	(0.008)	(0.011)
$Female$	0.125***	–0.041***	–0.058***
	(0.007)	(0.006)	(0.005)
Peer effects$_s$	0.097***	0.128***	0.219***
	(0.006)	(0.005)	(0.008)
$Constant$	0.263***	0.254***	0.364***
	(0.046)	(0.037)	(0.055)
PSLE score instrumented	Yes	Yes	Yes
'*Primary school* × *PSLE score* × *Cohort*' fixed effects	Yes	Yes	Yes
N	635,112	635,112	635,112
R^2	0.639	0.75	0.765

Notes: The first six columns apply a standard value-added specification, whereas the last three columns apply a flexible value-added model. *PSLE score* is the subject-specific exam score in primary school. When applying the IV approach, *PSLE score* is instrumented by the exam scores in all other primary school subjects. In addition to the subjects mentioned, exam scores in community knowledge and science are used as instruments. *Peer effects*$_s$ is the average primary school subject-specific exam score for a student's secondary school schoolmates. *PSLE score*, *Peer effects*, and the dependent variables are standardized by their sample means and standard deviations. Standard errors are clustered at the secondary school level. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Source: author's calculations.

Appendix B: supplementary robustness analyses

The following supplementary material includes different robustness analyses interacting the private secondary school enrolment dummy with different geographical areas, primary school type, peer effects, a religious school dummy, and a same-gender school dummy. Finally, the preferred model is estimated separately for each cohort.

Geographical heterogeneity

The literature finds that lagged achievement captures the majority of relevant student and family characteristics. One may, however, still worry that students attending private secondary schools belong to families who suddenly became wealthier and then were able to afford other educational inputs like private schooling and private tuition. As income changes may differ in urban settings compared to smaller towns and villages, one robustness test investigates heterogeneity in the private school learning premium in regard to urbanization.[17] In addition, data from Tanzania National Panel Surveys in 2013 and 2015 are used to identify regions with the most severe consumption changes. Despite the survey data being only nationally—and not regionally—representative, two additional models extending the preferred model in the main text are estimated: (1) including interactions between the private school dummy and two dummies indicating whether a student lives in a top or bottom region in terms of consumption growth; (2) including an interaction between the private school dummy and the consumption growth rate in the region where the student lives.[18] There are substantial breaks between both the regions with the second lowest and third lowest consumption growth rate, and the regions with the second highest and third highest consumption growth rate. This makes natural breaking points for the robustness analysis.

Table B1 presents the results from the above-mentioned models. From column (1) it is clear that urban areas have a smaller private school learning premium compared to smaller towns and villages. This is in line with Singh's (2015) finding that rural areas in India have a higher private school learning premium. From column (2) one sees that high-growth and low-growth regions have a similar learning premium as other regions. When interacting the private school dummy with consumption growth in column (3), however, the interaction term becomes significant at the 10 per cent significance level. With consumption growth rates between -22 and 17 per cent, the maximum effect of consumption growth on the learning premium is considered to be modest.

One-off impact of private schools

Andrabi et al. (2011) examined the impact of Pakistani primary school students switching between public and private schools. In a difference-in-differences model, they compare test score gains for students between third and fourth grade, and between third and fifth grade. The one-year gains (comparing test scores between third and fourth grade) from switching to a private school are 0.26–0.31 of a standard deviation, whereas the two-year gains are only slightly higher. The authors argue this is due to low persistence in test scores. While low persistence may explain some of the lower gains in the second year of private schooling, it seems implausible that low persistence should cause as small academic gains in

[17]Urbanization is defined as cities with more than 100,000 inhabitants, which include Dar es Salaam, Arusha, Mwanza, Mbeya, Morogoro, Tanga, Kigoma, Dodoma, and Songea.

[18]The top regions in terms of consumption growth are Singida and Mbeya, while the bottom two regions are Iringa (including Njombe Region) and Kilimanjaro.

Table B1: Analysis of geographical heterogeneity

Dependent variable: GPA_s $(FTNA)$	(1)	(2)	(3)
$Private_s$	0.504***	0.434***	0.466***
	(0.016)	(0.016)	(0.017)
$Peer\ effects_s$	0.152***	0.154***	0.153***
	(0.005)	(0.005)	(0.005)
$GPA\ other_p$ *(PSLE)*	0.222***	0.223***	0.223***
	(0.002)	(0.002)	(0.002)
$Urban_s$	0.060***		
	(0.012)		
$Private_s \times Urban_s$	–0.171***		
	(0.023)		
$High\ growth_s$		0.036*	
		(0.019)	
$Low\ growth_s$		0.044***	
		(0.016)	
$Private_s \times High\ growth_s$		0.056	
		(0.045)	
$Private_s \times Low\ growth_s$		0.038	
		(0.028)	
$Growth_s$			–0.001***
			(0.001)
$Private_s \times Growth_s$			0.002*
			(0.001)
'*Primary school* × *Primary school GPA* × *Cohort*' fixed effects	Yes	Yes	Yes
N	635,112	635,112	635,112
R^2	0.739	0.739	0.739

Notes: GPA_s is the GPA of the subjects Kiswahili, English, and mathematics. $Peer\ effects_s$ is the average GPA of the subjects Kiswahili, English, and mathematics in primary school for secondary school schoolmates. $GPA\ other_p$ is the GPA of the subjects community knowledge and science in primary school. $Peer\ effects_s$, $GPA\ other_p$, and GPA_s are standardized by their sample means and standard deviations. $High\ growth_s$ is a dummy taking the value 1 if the school is located in Singida or Mbeya, whereas $Low\ growth_s$ is a dummy taking the value 1 if the school is located in Iringa, Njombe, or Kilimanjaro. $Growth_s$ is a continuous variable measuring consumption growth between 2013 and 2015 for the region in which the school is located. The models further account for secondary school size and student gender. Standard errors are clustered at the secondary school level. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Source: author's calculations.

the second year as the authors find. Another explanation for the lower academic gains in the second year of private schooling could be that private schools pick the low-hanging fruit in terms of improving students' test scores in the first year. Irrespective of the exact reasons for lower academic gains in the second year, the results suggests that one should try to distinguish between students coming from private and public schools when estimating the private school learning premium.

Table B2 estimates the private school learning premium separately for students attending public primary school and students attending private primary school. The results suggest the impacts of private schools are larger for students who went to public primary school. The coefficient estimate is around twice the size for public primary school students compared to private primary school students. These results are in line with Andrabi et al.'s (2011) finding that the private school learning premium is larger in the first year of private schooling.

Table B2: Analysis of primary school type heterogeneity

Dependent variable: GPA_s $(FTNA)$	(1)
$Private_s$	0.495***
	(0.015)
$Private_s \times Private_p$	–0.243***
	(0.020)
log(School $size_s$*)*	–0.089***
	(0.007)
Female	0.057***
	(0.005)
Peer $effects_s$	0.156***
	(0.005)
GPA $other_p$ *(PSLE)*	0.223***
	(0.002)
‘*Primary school* × *Primary school GPA* × *Cohort*’ fixed effects	Yes
N	620,857
R^2	0.738

Notes: Primary school type could not be determined for 14,255 students. GPA_s is the GPA of the subjects Kiswahili, English, and mathematics. *Peer* $effects_s$ is the average GPA of the subjects Kiswahili, English, and mathematics in primary school for secondary school schoolmates. *GPA* $other_p$ is the GPA of the subjects community knowledge and science in primary school. *Peer* $effects_s$, *GPA* $other_p$, and GPA_s are standardized by their sample means and standard deviations. Standard errors are clustered at the secondary school level. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Source: author’s calculations.

Private schools capitalizing on peer effects

The current paper has endeavoured to distinguish any private school learning premium from peer effects. The premise has been that private schools are in essence not better than public schools if shifting the student populations would make public schools perform better than private schools. While private schools may improve students’ exam scores through both peer effects and a more genuine private school learning premium, the two mechanisms could also jointly affect students’ exam scores. Given either public schools or private schools are better at capitalizing on peer effects, the interaction term between the two mechanisms is relevant to include in the model.

Table B3 presents the results from a model including the interaction between private schooling and peer effects. The coefficient estimate associated with the private school learning premium remains similar to the coefficient estimate in the preferred model. Interestingly, private schools have a significantly higher coefficient estimate associated with peer effects. As discussed in the methodology section, this does not necessarily mean that private schools are better at capitalizing on peer effects as the peer effect variable could be capturing family-supplied inputs. The minimum and maximum value of the peer effects variable are -2.8 and 4.2, respectively. Consequently, the private school learning premium is positive independent of current peers.

Heterogeneity on other observables

The current robustness analyses test whether schools offering religious courses have a higher or lower private school learning premium than schools not offering religious courses, whether same-gender schools vary from mixed-gender schools, and whether cohorts are distinctively different. In the religion analysis, the private school dummy is interacted with a dummy telling whether or not a school

Table B3: Analysis with private school and peer effects interaction

Dependent variable: GPA_s $(FTNA)$	(1)
$Private_s$	0.405***
	(0.013)
$Peer\ effects_s$	0.124***
	(0.006)
$Private_s \times Peer\ effects_s$	0.080***
	(0.009)
$log(School\ size_s)$	–0.078***
	(0.007)
$Female$	0.058***
	(0.005)
$GPA\ other_p$ $(PSLE)$	0.223***
	(0.002)
'*Primary school* $\times$ *Primary school GPA* $\times$ *Cohort*' fixed effects	Yes
N	635,112
R^2	0.739

Notes: GPA_s is the GPA of the subjects Kiswahili, English, and mathematics. $Peer\ effects_t$ is the average GPA of the subjects Kiswahili, English, and mathematics in primary school for secondary school schoolmates. $GPA\ other_{t-1}$ is the GPA of the subjects community knowledge and science in primary school. $Peer\ effects_t$, $GPA\ other_{t-1}$, and GPA_t are standardized by their sample means and standard deviations. Standard errors are clustered at the secondary school level. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Source: author's calculations.

offers elective courses in either Bible knowledge or Islamic knowledge. This 'religious courses' dummy is further divided into a 'Bible course' dummy and an 'Islamic course' dummy. Similar to the religion analysis, the same-gender analysis interacts the private school dummy with a dummy stating whether a school is a same-gender school. This same-gender school dummy is further divided into girls-only schools and boys-only schools. Finally, due to a major secondary school reform taking place at the beginning of 2016, the three cohorts are examined separately. The 2015 cohort took the FTNA just before the implementation of the reform, whereas the 2016 cohort had attended secondary school for one year under the new reform, and the 2017 cohort had only attended secondary school under the new reform.

Table B4 shows the effects of attending schools offering religious courses compared to schools not offering religious courses. There seems to be no overall effect of schools offering religious courses neither in the public school sector nor in the private school sector. Examining schools offering Bible knowledge and Islamic knowledge separately, however, it becomes evident that schools offering Islamic knowledge have a lower private school learning premium. This result is independent of whether the religion dummy is based on at least one student, at least 25 per cent of students, at least 50 per cent of students, or at least 75 per cent of students attending the religious course. Despite the negative coefficient estimate on the interaction between private schooling and Islamic course, private schools offering Islamic knowledge still outperform public schools.

The effects of attending a same-gender school are presented in Table B5. Column (1) demonstrates that students attending same-gender secondary schools perform better than their mixed-gender counterparts. Furthermore, the private school learning premium is also higher for students attending same-gender schools. Columns (2), (3), and (4) illustrate students from both boys' schools and girls' schools generally perform better than students in mixed-gender schools, but it is mostly girls' schools that drive the higher private school learning premium. While the overall private school learning premium to some extent is driven by same-gender schools, column (1) also suggests that the private school learning premium for

Table B4: Analysis of secondary schools offering religious courses

Dependent variable: GPA_s $(FTNA)$	(1)	(2)	(3)
$Private_s$	0.463***	0.444***	0.470***
	(0.017)	(0.015)	(0.015)
$Religious\ courses_s$	0.002		
	(0.010)		
$Private_s \times Religious\ courses_s$	–0.033		
	(0.022)		
$Bible\ course_s$		0.004	
		(0.016)	
$Private_s \times Bible\ course_s$		0.019	
		(0.027)	
$Islamic\ course_s$			–0.004
			(0.010)
$Private_s \times Islamic\ course_s$			–0.143***
			(0.029)
$log(School\ size_s)$	–0.084***	–0.084***	–0.082***
	(0.007)	(0.007)	(0.008)
$Female$	0.058***	0.057***	0.058***
	(0.005)	(0.005)	(0.005)
$Peer\ effects_s$	0.154***	0.153***	0.151***
	(0.005)	(0.005)	(0.005)
$GPA\ other_p$ *(PSLE)*	0.223***	0.223***	0.223***
	(0.002)	(0.002)	(0.002)
'*Primary school* $\times$ *Primary school GPA* $\times$ *Cohort*' fixed effects	Yes	Yes	Yes
N	635,112	635,112	635,112
R^2	0.739	0.739	0.739

Notes: *Religious courses* is an indicator for whether the school offers either Bible knowledge or Islamic knowledge as elective courses. GPA_s is the GPA of the subjects Kiswahili, English, and mathematics. $Peer\ effects_s$ is the average GPA of the subjects Kiswahili, English, and mathematics in primary school for secondary school schoolmates. $GPA\ other_p$ is the GPA of the subjects community knowledge and science in primary school. $Peer\ effects_s$, $GPA\ other_p$, and GPA_s are standardized by their sample means and standard deviations. Standard errors are clustered at the secondary school level. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Source: author's calculations.

mixed schools is close to the result in the preferred model in the main text. The difference between the two coefficient estimates is found to be insignificant.

Table B6 presents the results from studying the cohorts in separate regression models. There are only small deviations in the results between the three years. While the coefficient estimate on private schooling drops from 2015 to 2016, the change is insignificantly different from zero. The 2017 cohort was fully affected by the new reform in 2016. This led to a substantial increase in enrolment into public secondary schools. Assuming this increase in enrolment had negative effects on quality of education, as seemed to be the case when Tanzania introduced free primary school, one would expect the private school learning premium to increase in 2017. In line with expectations, the private school learning premium is significantly higher in 2017 compared to the two previous years.

Table B5: Analysis of same-gender secondary schools

Dependent variable: GPA_s $(FTNA)$	(1)	(2)	(3)	(4)
$Private_s$	0.432***	0.453***	0.428***	0.431***
	(0.014)	(0.014)	(0.014)	(0.014)
$Same\ gender\ school_s$	0.120***			
	(0.031)			
$Private_s \times Same\ gender\ school_s$	0.096***			
	(0.036)			
$Boys\ school_s$		0.097		0.141**
		(0.060)		(0.062)
$Private_s \times Boys\ school_s$		–0.006		0.030
		(0.068)		(0.070)
$Girls\ school_s$			0.074**	0.104***
			(0.031)	(0.029)
$Private_s \times Girls\ school_s$			0.130***	0.130***
			(0.037)	(0.036)
$log(School\ size_s)$	–0.067***	–0.081***	–0.075***	–0.067***
	(0.007)	(0.007)	(0.007)	(0.007)
$Female$	0.052***	0.061***	0.047***	0.051***
	(0.005)	(0.005)	(0.005)	(0.005)
$Peer\ effects_s$	0.132***	0.148***	0.144***	0.133***
	(0.005)	(0.005)	(0.005)	(0.005)
$GPA\ other_p\ (PSLE)$	0.222***	0.223***	0.222***	0.222***
	(0.002)	(0.002)	(0.002)	(0.002)
'*Primary school* × *Primary school GPA* × *Cohort*' fixed effects	Yes	Yes	Yes	Yes
N	635,112	635,112	635,112	635,112
R^2	0.739	0.739	0.739	0.739

Notes: GPA_s is the GPA of the subjects Kiswahili, English, and mathematics. $Peer\ effects_s$ is the average GPA of the subjects Kiswahili, English, and mathematics in primary school for secondary school schoolmates. $GPA\ other_p$ is the GPA of the subjects community knowledge and science in primary school. $Peer\ effects_s$, $GPA\ other_p$, and GPA_s are standardized by their sample means and standard deviations. Standard errors are clustered at the secondary school level. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Source: author's calculations.

Table B6: Cohorts analysed separately

Dependent variable: GPA_s $(FTNA)$	(1)	(2)	(3)	(4)
$Private_s$	0.418***	0.397***	0.523***	0.422***
	(0.020)	(0.017)	(0.019)	(0.017)
$Private_s \times Cohort16$				–0.009
				(0.018)
$Private_s \times Cohort17$				0.085***
				(0.018)
log(School size$_s$)	–0.075***	–0.090***	–0.080***	–0.082***
	(0.013)	(0.009)	(0.009)	(0.007)
Female	0.103***	0.047***	0.036***	0.057***
	(0.006)	(0.006)	(0.007)	(0.005)
Peer effects$_s$	0.158***	0.168***	0.138***	0.152***
	(0.007)	(0.007)	(0.006)	(0.005)
GPA other$_p$ (PSLE)	0.205***	0.202***	0.247***	0.223***
	(0.004)	(0.003)	(0.003)	(0.002)
'*Primary school × Primary school GPA*' fixed effects	Yes	Yes	Yes	Yes
FTNA cohort	2015	2016	2017	All
N	176,112	198,316	260,684	635,112
R^2	0.752	0.75	0.722	0.739

Notes: *GPA$_s$* is the GPA of the subjects Kiswahili, English, and mathematics. *Peer effects$_s$* is the average GPA of the subjects Kiswahili, English, and mathematics in primary school for secondary school schoolmates. *GPA other$_p$* is the GPA of the subjects community knowledge and science in primary school. *Peer effects$_s$*, *GPA other$_p$*, and *GPA$_s$* are standardized by their sample means and standard deviations. Standard errors are clustered at the secondary school level. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Source: author's calculations.