Economic inequality, teacher truancy and learning: Evidence from Sub-Saharan Africa

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Abstract

Widespread evidence emphasizes the prevalence of teacher absenteeism in developing countries. We estimate the impact of teacher truancy on the reading and mathematics achievement of primary school students in eight African countries. As development priorities shift from enrollment to learning, it is critical to identify, among the potential barriers faced by students in developing countries, those which impede the learning process. We find that teacher truancy has no average effect on test scores. Rather, it is detrimental only to students from households belonging to the uppermost percentiles of the socioeconomic distribution. A robustness check based on an IV approach confirms these findings. These conclusions beg consideration from policy-makers, particularly for those countries with large proportions of students in the bottom of the socioeconomic distribution. They suggest that it is solely when inequalities in educational opportunities are reduced that encouraging teacher attendance plays a significant role in determining educational outcomes.

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1 Introduction

Widespread evidence attests to the prevalence of teacher absenteeism in developing country schools. Relying on the World Bank's World Absenteeism Survey of six countries in 2002 and 2003, Chaudhury, Hammer, Kremer, Muralidharan, and Rogers (2006) found teacher absence rates to be 19% or one out of five days on average. Even when present, many teachers were discovered to be engaged in activities other than teaching, such as reading the newspaper or talking to colleagues. More recently, the World Bank's Service Delivery Indicators report that, in 2013 and 2012, the share of teachers present in the classroom out of those teachers at school during scheduled teaching hours was 52.5% in Uganda and 42.2% in Kenya.[1] Even when official codes of conduct do exist to curb such unprofessionalism, they are rarely disseminated or enforced (van Nuland (2009)).

The objective of this paper is to estimate the impact of teacher truancy (tardiness, absenteeism, and skipping class) on students' academic performance in a set of eight African countries. As development priorities shift from enrolment to learning, it is critical to identify, among the many potential barriers faced by students in developing countries, those which impede the learning process.

Raw evidence suggests teacher truancy to be correlated with poor student achievement. For instance in India, where teacher absenteeism is high, the NGO Pratham tested the knowledge levels of 700,000 children, interviewed across all 600 Indian districts. The results, obtained in 2005, demonstrate an unsurprisingly dismal picture of learning levels: Among the 7 to 14 age group, 35% could not read a simple paragraph (first grade level), and almost 60% of children could not read a simple story (second grade level). Only 30% were competent

[1] For further information on the Service Delivery Indicators, see: `http://datatopics.worldbank.org/sdi/`.

in second-grade mathematics (basic division). Kremer, Chaudhury, Rogers, Muralidharan, and Hammer (2005) confirm the negative correlation between teacher absenteeism and educational achievements in India. They show that an increase in teacher absence by 10% correlates to a reduction in test scores by a standard deviation of 0.2. Unfortunately, such correlations are not limited to India. Similar outcomes have been found in other low-income countries where absenteeism is rife. For example, Uwezo's 2011 report in Tanzania documents that only 4 out of 5 teachers were present in school visits. In their survey of over 128,000 children, only 1 in 10 third grade pupils could read a basic English story while only 3 in 10 could add, subtract, and multiply.

Despite anecdotal links to achievement, one might wonder if teacher conduct plays a substantial role in the learning outcomes of the average student. Changes to school inputs do not necessarily translate into learning gains, especially for students from poorer backgrounds (Glewwe, Kremer, and Moulin (2009), Kuecken and Valfort (2013)). As detailed extensively in the following section, a combination of factors stemming from poverty, including poor early childhood development, inconsistent schooling due to negative income shocks, elitist curriculum biases, and low expectations, may generate inequalities of opportunity and impede learning for poorer students regardless of teacher conduct. This suggests that the effect of teacher truancy on student achievement might concern only wealthier pupils.

Considering this conjecture, our paper seeks to improve upon the scarce literature on the impact of teacher truancy on educational achievements in developing countries. We do so in three ways. First, we focus on eight countries, while previous studies have been limited to single countries. Second, our empirical strategy aims to resolve a host of endogeneity issues that only one previous randomized control trial was able to explicitly address. Third, we are

the first to analyse the heterogeneous impact of teacher truancy on educational achievements according to students' socioeconomic status ("SES" hereafter).

To estimate the impact of teacher truancy on students' academic achievement as well as its potential heterogenous effect across students' SES, we use a set of eight countries from the Southern and Eastern African Consortium for Monitoring Educational Quality (SACMEQ) survey from 2000. This initiative administers standardized tests in reading and mathematics and conducts student, teacher, and school director surveys. Notably, these surveys report the frequency with which eight specific teacher misbehaviours[2] occur at school. We focus here on all misconduct related to attendance. Other types of misbehaviour, such as bullying or sexual harassment, might be expected to have ambiguous effects on achievement.[3] Moreover, these other categories of misconduct are particularly prone to misreporting.

We proceed first with a simple ordinary least squares (OLS) analysis, knowing that it might produce biased estimates if teacher truancy is endogenous. This concern arises in four ways: First, underlying factors may influence both teacher truancy and student achievement at either the school level (e.g. student misbehaviour) or at a higher level (e.g. parents' trust in the schooling system). Second, teachers have preferences regarding their placements in schools and may manage to fulfil them. Indeed, official protocol dictating placements is often not followed in practice. If, in a given country, all teachers prefer to work in the best schools, we risk overestimating the negative impact of teacher truancy on student achievement if only the best-behaved teachers are placed in the best schools. This

[2]These include the frequency of tardiness, absenteeism (unjustified absences), skipping class, intimidation or bullying of pupils, sexual harassment of students by teachers, use of abusive language, drug abuse, and alcohol abuse or possession.

[3]For example, bullying students may inhibit their capacity to learn if they are too discouraged or, alternatively, incentivise students to work harder out of fear of retaliation. Similarly sexual harassment, which is a priori detrimental to student success, may be accompanied by compensation such as individual supervision, reduction of school fees, or supply of gifts that could improve learning.

selection bias can be compounded by a second one, whereby the best performing students go to schools in their locality where teacher truancy is the lowest. This process would again lead to an overestimation of the negative impact of teacher truancy on test scores. Third, a teacher's behavioural decisions might be reflective of the quality of his or her students. Higher achieving students could motivate teachers to come to school or, conversely, reduce their incentives to maintain good behaviour. Finally, indicators of attendance may suffer from measurement error due to inaccurate or biased reporting.

Our OLS analysis mitigates omitted variables bias by controlling for a large set of characteristics at the student, class, teacher and school level, as well as for regional fixed effects. To limit selection bias, we control for the quality of the school, as proxied by the average test score obtained by all students. This simple analysis reveals that teacher truancy has no average effect on test scores. It is instead detrimental only to students from households belonging to the uppermost percentiles of the socioeconomic distribution. But, while descriptive, an OLS strategy remains incapable of mitigating the potential reverse effect of student achievement on teacher truancy as well as the measurement error problem.

We therefore perform a robustness check that relies on an instrumental variables (IV) approach. As Nunn and Wantchekon (2011) find that historic exposure of ethnic groups to the slave trade leads to significantly lower levels of trust among those same groups today, we use regional slave trade exposure as an instrument for teacher truancy. We expect trust to be highly correlated with truancy since trust has been shown to determine cooperation. To be sure, the slave trade can impact student achievement via competing channels, so we control for these additional channels at both the school and regional levels. The results from the first-stage of our two-stage least squares approach confirm that regional slave trade exposure

is an important determinant of truancy. Moreover, the two-stage results confirm that teacher truancy has no average effect on test scores. It is only when we interact this measure with students' socioeconomic levels that we observe an impact: the negative effect of truancy only exists for those students in the 83rd percentile of the socioeconomic distribution and above for math and in the 77th percentile and above for reading. Our results are robust to a relaxation of the exclusion restriction.

The paper proceeds as follows: Section 2 discusses related literature. In Section 3, we introduce our dataset. We present our OLS results in Section 4. We develop our instrumental variables robustness check in Section 5. Finally, Section 6 summarizes our results and their policy implications as well as highlights avenues for future research.

2 Related literature

2.1 The effect of teacher truancy on learning

To the best of our knowledge, only two previous studies have analysed the impact of teacher truancy on educational achievements in developing countries:

Das, Dercon, Habyarimana, and Krishnan (2007) use two-period panel data from Zambia to measure the impact of teacher absence rates on student test scores. Their data structure allows them to control for students' time-invariant characteristics and therefore to limit the omitted variable bias. Their results on the whole sample are consistent with ours: they find no effect of teacher absenteeism on educational achievements. However, their approach does not allow them to control for a change in unobserved teacher characteristics across both periods, a concern that occurs when students are taught by a different teacher in period 1

and in period 2. To avoid this problem, the authors restrict their attention to the subsample of pupils with the same teacher in both periods.[4] Using this restricted sample, they find a negative impact of teacher absence on learning in English and mathematics during the academic year studied. This result is at odds with ours. However, Das et al. (2007)'s focus on the restricted sample does not allow them to treat the potential reverse causality bias. In this context, their results may simply be driven by the fact that better performing students increase teachers' incentives to maintain good behaviour (and conversely), a pattern particularly likely to emerge in the long run, i.e. if the same students are matched with the same teacher for more than one academic year.

The second study is a randomized controlled trial conducted in India by Duflo, Hanna, and Ryan (2012). The authors show that discouraging teacher absenteeism through monetary incentives for presence and sanctions for absence does cause higher student achievement. Yet, unlike us, they do not focus on standard primary schools but on single teacher informal education centres built in remote areas. It may therefore be that teachers sent to such areas are trained to make curriculum more digestible to poor students given that the centres are targeted for the poor. Moreover, since teachers are alone, they do not have as many potential in-school distractions (such as socializing with other colleagues).

This short overview suggests that the question of the impact of teacher truancy on educational achievement in a representative set of primary schools in low-income countries has not yet been resolved. We aim to develop a more comprehensive answer.

[4]They do so after having taken care to ensure that the subsample of pupils with the same teacher in both periods and the subsample of pupils with different teachers in both periods are similar, at least in terms of observed characteristics.

2.2 The relationship between student SES and learning

Students from poorer backgrounds are typically characterized by lower levels of academic achievement. In Ghana, for instance, Chowa et al. (2013) show that students from households with more assets perform better in English than disadvantaged students. Thus, in relatively disadvantaged contexts, teacher truancy may be of little consequence. In particular, several factors may explain why poorer students are less likely to be influenced by their teachers' attendance.

First, students from impoverished households are more likely to experience obstacles to early childhood development. A vast literature shows that health problems in early childhood negatively affect cognitive and non-cognitive development later in life.[5] This, in turn, can have lasting effects on both schooling attainment and performance (Fletcher (2011)).

Second, when negative income shocks arise, it is the poorest households that make the largest cuts to educational spending. Thomas, Beegle, Frankenberg, Sikoki, Strauss, and Teruel (2004) document this behaviour in Indonesia. Economic hardships cause disproportionate interruptions and delays in the schooling of relatively poorer children, particularly those with older siblings. Frequent interruptions inhibit future progression through school. In contrast, consistent education exhibits a path dependency which increases the likelihood of future educational attainment (Mani, Hoddinott, and Strauss (2012)).

Third, as has been well-documented, developing country curricula are characterized by strong elitist biases that derive from colonial practices of favouring a small elite over local populations. This bias, now institutionalized into modern day curricula, has increased over time. Emphasis is continually placed on ambitious curricula that leave a vast majority of

[5] See Barker (1994) for the origins of this path dependency from early childhood development to lifetime health.

students behind, particularly those from lower socioeconomic levels (Glewwe, Kremer, and Moulin (2009), Banerjee and Duflo (2011)). Thus, when faced with poorly adapted curricula, students from disadvantaged backgrounds may fail to succeed regardless of teacher truancy, particularly if no effort is made by the teacher to adapt the material to all learning levels.

These problems are further compounded by the fact that teachers maintain, on average, low expectations about the ability of poor students to succeed (Hanna and Linden (2012)) and do not exert effort to make material more accessible for them. In this context, teacher misbehaviour may be detrimental only for students from more privileged backgrounds who are able to keep pace with curricula and maintain good favor with teachers (and therefore receive more academic assistance) (Banerjee and Duflo (2011)). High parental expectations about their children's ability to succeed may be able to counter these low expectations and disadvantaged backgrounds (Zhan (2006), Benner and Mistry (2007)). However, there is some evidence that parents in poor households themselves concentrate their energy on only one child to the detriment of the others, not only due to credit constraints but also due to low expectations in their children's propensity for achievement (see Banerjee and Duflo (2011)). For instance, Barrera-Osorio et al. (2011) analyse the impact of offering conditional cash transfers (CCT) on students' academic achievements in Colombia.[6] These authors find that participation in CCTs causes a worrisome rivalry among siblings: brothers, and particularly sisters, of treated students attend school less frequently and drop out more often than those in families that received no treatment.

Taking the combination of these factors into account – poor early childhood development in underprivileged households, removal of children from school when such households face

[6]Under these programs, students are paid on a monthly or bi-monthly basis for meeting a specified attendance target.

negative income shocks, elitist curriculum biases, and globally low expectations for poorer students – suggests that the effect of teacher truancy on student achievement might concern only wealthier pupils. We explore this possibility in our analysis.

3 Data

We use the second round of the Southern and Eastern African Consortium for Monitoring Educational Quality survey, conducted in 2000.[7] SACMEQ itself is a partnership of 15 Ministries of Education that collaborate on educational expertise and scientifically monitor educational progress. The SACMEQ II survey administered standardized reading and mathematics examinations to both students and teachers to compare cross-country achievement in the final year of primary school. Surveys also targeted the school directors, reading/mathematics teachers, and students, capturing a valuable array of additional school level information. Due to the fact that the instrumental variables technique using the regional intensity of slave exports compiled by Nunn and Wantchekon (2011) accounts for only those countries in the Afrobarometer survey,[8] we limit our study to eight SACMEQ countries that are also included in the Afrobarometer survey: Botswana, Kenya, Malawi, Mozambique, Namibia, Tanzania, Uganda, and Zambia.[9] These countries encompass 27,800 students enrolled in the terminal year of primary school.

[7] We opt to use only SACMEQ II, and not SACMEQ I or III, as SACMEQ I reports no information on teacher misbehaviour, and SACMEQ III does not report labelled regions which are key for our robustness check.

[8] The Afrobarometer survey tracks trends in public attitudes regarding the social, political, and economic atmosphere.

[9] Officially, 14 countries constitute the SACMEQ network: Botswana, Kenya, Lesotho, Malawi, Mauritius, Mozambique, Namibia, Seychelles, South Africa, Swaziland, Tanzania (both the mainland and Zanzibar), Uganda, Zambia and Zimbabwe. Zimbabwe, however, was not a participant in the SACMEQ II survey. We are also forced to exclude Mauritius, Seychelles, and Swaziland since slave exports are missing for these countries. Moreover, we eliminate Lesotho since its slave exports are equal to 0 (and thus cannot be meaningfully instrumented in a within-country analysis) as well as South Africa as it reports no test scores for teachers, a crucial control variable.

3.1 Student performance

To measure educational outcomes, our dependent variables are the reading and mathematics scores obtained by students on standardized tests. These scores, presented in Panel A of Table 1, are normalized using Rasch scaling[10] which places all test items administered in the surveys on a single scale for each subject. Though these measures unfortunately do not allow us to compute a value-added measure of learning achievement, they do allow us to compare learning achievement across countries.

3.2 Teacher truancy

Our measure of teacher truancy derives from three survey questions posed to the school director about the frequency with which he or she observes certain teacher behaviours (3 if often, 2 if sometimes, and 1 if never). We take the average of three questions that report how often the school director observes teacher tardiness, absenteeism, and skipping class. Table 2 reports the summary statistics for the three types of truancy as well as the average (1.76).

There are several limitations to our measure of truancy. First, it is likely that these values are underestimated. While targeting the school director eliminates to some degree problems associated with dishonest self-reports of teachers, it is equally possible that directors themselves intentionally under-report negative behaviours so as to avoid portraying their leadership in a bad light. Directors could also unintentionally under-report truancy if certain practices are institutionalized and simply attract little of their attention. Closely

[10]Rasch models are used in item response theory to produce ability measures (e.g. test scores) by controlling for the difficulty of questions on a test using logistic estimation. In this way, Rasch scores fully characterize individual ability and are often used instead of traditional test scores.

related is the issue that our measure of truancy relies on a director's perception of frequency rather than upon observed infractions directly. This method leads to measures that are coarser than would otherwise be preferred.

Studies of absenteeism typically rely on spot checks that document the number of absent teachers on the day of the survey. Yet spot checks are not necessarily reliable either. In their study of teacher absenteeism in Zambia, Das, Dercon, Habyarimana, and Krishnan (2007) compare three different methods of absenteeism reporting: spot checks, teacher self-reports, and head teacher reports. Spot checks, the authors conclude, are noisy because they capture only one moment in time. Teacher self-reports, on the other hand, are biased because they cannot record reports of any teachers absent on the day of the survey and, furthermore, fall prey to under-reporting by chronic offenders. The authors therefore opt to use head teacher reports of absenteeism (over the past 30 days) in their analysis. This comparison provides us with reassurance that, although imperfect, reports from the school director may circumvent reporting bias to the best extent possible.

Regardless, under-reporting could limit our ability to find a significant impact of teacher truancy on test scores. By reducing the variation in teacher truancy, reporting bias increases the risk of a type II error (the failure to reject a false null hypothesis). The fact that we find a consistent effect of truancy on test scores across student SES encourages us that such a type II error is avoided.

Finally, aggregating tardiness, absenteeism, and skipping class into a single average will be problematic if this aggregation dampens the variation in teacher truancy. To examine if this is the case, we compute an alternative truancy measure using principal components analysis (PCA) as part of the additional robustness checks presented in the supplementary

appendix. As our conclusions hold with PCA, we opt for the more straightforward choice of the simple average.

Despite these indications that our teacher truancy measure may not be as bad as one initially thinks, measurement error remains a likely source of endogeneity. Indeed, it is reasonable to expect that directors of low quality schools are liable to under-report teacher truancy in order to create an illusion of school quality, thereby biasing the effect of teacher misbehaviour on student performance. Our IV approach aims to treat this measurement error issue.

3.3 Other controls

As a large number of other educational characteristics may be correlated to both student achievement and teacher truancy, we include a variety of controls at the student, classroom, teacher, and school levels. Moreover, we control for regional fixed effects[11] in our OLS approach.[12]

At the student level, shown in Panel B of Table 1, we control for demographic information such as sex (using an indicator for whether or not the student is female) and age. The average age is 14.22 years old. Relative to the official primary school enrolment age of 6-7 in this group of countries, students are slightly over-age on average.[13] We also control for student socioeconomic status with a proxy, employing an average of all of the home possessions (14 in total) present in the student's household (newspaper, magazine, radio, television, VCR, cassette, telephone, refrigerator, car, motorcycle, bicycle, water, electricity, and table). As

[11]There are 67 regions in our dataset: 7 in Botswana, 8 in Kenya, 3 in Malawi, 11 in Mozambique, 13 in Namibia, 12 in Tanzania, 4 in Uganda, and 9 in Zambia.

[12]Because our instrument is defined at the regional level, we cannot include regional fixed effects in the IV strategy. However, we control instead for a comprehensive set of regional characteristics.

[13]See the UNESCO Institute for Statistics for further information: `http://www.uis.unesco.org/`.

might be expected, the mean level of home possessions is relatively low (at 0.33). Finally, we add an indicator variable for whether or not a student has access to a textbook, by ownership or by sharing, and note that there is little difference across subjects with respect to the average student's chance of having books available.

In Panel C, we control for class characteristics such as size and ratio of girls within each class – the average class contains roughly 43 students, with girls comprising only about 10% of a class on average. This information is followed by math and reading teacher characteristics in Panels D and E, respectively. Regarding teachers, we account for sex (using an indicator for females), age, and highest level of academic qualification obtained (with dummy variables for primary, junior secondary, senior secondary, and A-level/tertiary). On the whole, both math and reading teachers share the same mean age of 35, and, on average, the majority have completed a senior secondary level of education. As teachers are also subjected to standardized math and reading examinations as their students, we use the raw teacher test scores[14] as a proxy for teacher competency. Additionally, we include an average of classroom resources that each teacher has at their disposal. Eight dummy variables indicate the presence of the following items: writing board, chalk, wall chart, cupboard or locker, one or more bookshelves, classroom library or book corner, teacher table, teacher chair. On average, math and reading teachers have access to the same amount of classroom resources.

Finally, in Panel F we take into account a variety of controls at the school level. First, we consider the school director's sex (using an indicator for females), age, years of experience, and dummy variables for the highest level of academic qualification attained. On average, directors are predominantly male, 44 years of age, and graduates of senior secondary education complemented by two decades of experience. Second, we include variables for school

[14]This is measured as the number of correct responses out of a total of 41 for math and 47 for reading.

location (using an indicator if the school is in an urban area), school condition (with an indicator if the school is in good condition or needs only minor repair), and resources (an average of whether the school possesses 23 resources such as a library, staff room, first aid kit, etc.). Third, we control for other types of misconduct at school. Importantly, we compute teacher violence, which we use as a catch-all term for physical and verbal abuse. We take the average of three questions that report how often the school director observes intimidation or bullying of pupils, sexual harassment of students by teachers, and use of abusive language. Table 3 shows that violence and truancy are positively and significantly related, which is to be expected, with a correlation at the school level of roughly 52%. Though it is highly likely that violence measures are under-reported since they are more subjective, less directly observable, and potentially more controversial to acknowledge, when we estimate the effect of teacher truancy on test scores, we always control for teacher violence in case omitting this secondary dimension of misbehaviour removes crucial information.[15] We also construct the frequency of student misbehaviour as reported by the directors of each school: that which could affect individual test scores directly (tardiness, absenteeism, skipping class, classroom disturbances, bullying staff, injuring staff, sexually harassing teachers) and that which could affect peers' test scores (bullying others, sexually harassing others, fighting with others) by damaging self-confidence and creating a negative learning environment. We then compute an average of the frequency, as reported by the director of each school, with which the local community participates in in-kind and financial support activities such as building and maintaining the facility, providing supplies like equipment/furniture, stationary, and school meals, paying fees for exams and teacher/staff salaries, and teaching or participat-

[15]To alleviate any concerns that our results might be influenced by multicollinearity between truancy and violence, we also find that our results on the impact of teacher truancy on test scores hold even without controlling for teacher violence. These results are available upon request.

ing in extracurricular activities. Finally, in order to limit the selection bias (in which the best-behaved teachers select into the best schools or the best-performing students select into schools with the lowest level of truancy), we control for the quality of the school with the average test score obtained by students enrolled in this school.

4 Main analysis

4.1 Average effect of teacher truancy

We might initially expect teacher tardiness and absenteeism to be negatively related to students' academic performance. Truancy can reflect an absence of instruction if no teaching occurs when a teacher is not present. It may also result in a lower quality of instruction if other teachers substitute for a missing teacher or teacherless classes are combined with others. Indeed, the bivariate correlation between teacher truancy and test scores is negative and significant (at 1%) for both math and reading. But, without accounting for omitted variables or selection bias, this significant relationship may not be robust to a more comprehensive OLS approach conducted at the student level. We run this OLS approach with Equation (1):

$$P_{ij} = a + b.M_s + \mathbf{X'_i}.\mathbf{c} + \mathbf{U'_c}.\mathbf{d} + \mathbf{W'_j}.\mathbf{e} + \mathbf{V'_s}.\mathbf{f} + \mathbf{R'}.\mathbf{g} + \epsilon_i, \tag{1}$$

where P_{ij} represents the score on the standardized test of student i in subject j ($j = \{\text{math}, \text{reading}\}$). The variable M_s stands for the average level of truancy observed among teachers in school s. To account for unobserved characteristics, we denote student, class, teacher, and other school controls by vectors $\mathbf{X_i}$, $\mathbf{U_c}$, $\mathbf{W_j}$, and $\mathbf{V_s}$. These vectors contain the

variables that are depicted in Table 1 in Panel B, C, D (or E), and F respectively. Moreover, we control for regional fixed effects denoted by **R**.

Tables 4 and 5 present the OLS estimates for mathematics and reading test scores, with controls introduced step-wise across five columns: first, average teacher truancy and violence at the school level (column 1), followed by student (column 2), class (column 3), teacher (column 4), and other school (column 5) controls. Regional fixed effects are included in every column, and standard errors are clustered at the school level.

Average truancy is positive but not significant in math and negative but not significant in reading.[16] On balance, these results confirm the intuition that teacher truancy does not make a difference across the board. But does a different pattern emerge when we allow for heterogeneous effects of teacher truancy across student socioeconomic status?

4.2 Heterogeneous effects of teacher truancy across student SES

Based on the literature on school inputs, we suspect that the role for teacher misconduct may be a marginal one such that teacher attendance may only make a significant difference for students from the most privileged backgrounds. Poor early childhood development, negative income shocks leading to schooling interruptions, elitist curriculum biases, and low parent and teacher expectations can place poorer students in a situation where academic success is difficult to achieve regardless of teacher conduct. To test this hypothesis, we introduce in Equation (1) an interaction term between average teacher truancy at the school level and a student's SES (the average level of possessions in the student's household) denoted by

[16]The absence of significance and direction of the signs hold when allowing for a correlation between the error terms of the math and reading equations with a seemingly unrelated regression (SUR). Results available upon request.

$M_s^* SES$.[17]

Table 6 presents our results. As expected, the coefficient of the interaction term $M_s^* SES$ is negative and significant (at the 5% and 1% confidence levels in math and reading respectively). This finding reveals that teacher truancy has a detrimental impact only for students with the highest SES. More precisely, we perform a series of Wald tests at the bottom of Table 6 that identify the percentiles of the SES distribution for which the impact of teacher truancy is significant.[18] For instance, considering the 90th percentile of home possessions, this Wald test consists in computing whether the sum of the coefficient of M_s and the level of home possessions corresponding to the 90th percentile (0.64) multiplied by the coefficient of $M_s^* SES$ is significantly different from 0.

This analysis shows that teacher truancy has a heterogeneous relationship with achievement depending on a student's SES level. Teacher truancy is negatively and significantly related with student achievement in the 77th percentile and above in math and in the 69th percentile and above in reading. These results are consistent with our expectations. However, columns (1) and (2) of Table 6 also show that teacher truancy is positively and significantly related with student achievement in the 42nd percentile and below in math and in the 27th percentile and below in reading. This finding is consistent with a bias from reverse causality, according to which better performing students lower teachers' incentives to maintain good behaviour. If this reverse causality is at stake, this means that the negative impact of teacher truancy on the educational achievements of richer students is strongly underestimated. And

[17] We control simultaneously for the interaction of teacher violence and student SES.

[18] A home possession level of 0 corresponds to the 1st percentile, 0.07 to the 2nd to 15th percentiles, 0.14 to the 16th to 27th percentiles, 0.21 to the 28th to 42nd percentiles, 0.29 to the 43rd to 57th percentiles, 0.36 to the 58th to 68th percentiles, 0.43 to the 69th to 76th percentiles, 0.50 to the 77th to 82nd percentiles, 0.57 to the 83rd to 86th percentiles, 0.64 to the 87th to 90th percentiles, 0.71 to the 91st to 93rd percentiles, 0.79 to the 94th to 96th percentiles, 0.86 to the 97th to 99th percentiles, 0.93 to the 99th percentile, and 1 to the 100th percentile.

indeed, the orders of magnitude stemming from our OLS analysis are low. If we consider the case of a student belonging to the 90th percentile of the home possession distribution, Table 6 shows that an increase in teacher truancy by one standard deviation leads to a decrease in a student's test score by only 0.01 standard deviations in both math and reading.[19]

Thus, while descriptive, we take these results with caution as a basic OLS strategy is unable to address this reverse causality problem. It is furthermore unable to treat the measurement error problem. To address these biases, we therefore turn to an instrumental variables approach in the following section.

5 An IV robustness check

5.1 Estimation strategy

We base our estimation strategy on two simple functions: one for student academic achievement and the other for teacher truancy. Equation (2) describes the test score of student i in subject j (P_{ij}) as a function of teacher truancy at the school level (M_s), as well as vectors of individual characteristics ($\mathbf{X_i}$), classroom characteristics ($\mathbf{U_c}$), teacher characteristics ($\mathbf{W_j}$), other school characteristics ($\mathbf{V_s}$), region characteristics ($\mathbf{Z_r}$), and country fixed effects ($\mathbf{C}$):

$$P_{ij} = P_{ij}(M_s, \mathbf{X_i}, \mathbf{U_c}, \mathbf{W_j}, \mathbf{V_s}, \mathbf{Z_r}, \mathbf{C}), \tag{2}$$

where $\mathbf{X_i}$, $\mathbf{U_c}$, $\mathbf{W_j}$ and $\mathbf{V_s}$ are defined as in Equation (1). We present the characteristics that are included in $\mathbf{Z_r}$ below. Furthermore, Equation (3) describes teacher truancy at the

[19] To arrive at these figures, we add the product of the coefficient of the interaction term, standard deviation of teacher truancy, and level of home possessions corresponding to the 90th percentile (i.e., 0.64) to the product of the coefficient of teacher truancy and standard deviation of truancy. We then divide this difference by the standard deviation for test scores (either for math or reading).

school level as a function of historic slave trade exposure at the regional level, denoted S_r:

$$M_s = M_s(S_r) \tag{3}$$

To be deemed a good instrument, S_r must satisfy two conditions: First, it must be correlated with M_s and, second, it must be orthogonal to any variables omitted from Equation (2). The combination of these two conditions implies that S_r has an impact on P_{ij} only through its impact on M_s. We develop these key conditions in more detail below.

5.1.1 The correlation between slave trade exposure and teacher truancy

Nunn and Wantchekon (2011) demonstrate that a greater intensity of past exposure to the transatlantic and Indian Ocean slave trades is a significant predictor of lower modern day trust levels. As the authors describe, slaves were not only captured through state-organized raids and warfare but also through individuals who kidnapped, tricked, and sold their own friends and family members. Such actions developed a culture of mistrust especially within ethnic communities that were the most exposed[20] (see Dercon and Gutierrez-Romero (2012) for further evidence that violence reduces trust in the African context). It should come as no surprise that this mistrust has remained intact for centuries as much evidence shows that such norms persist over time via cultural and familial transmission,[21] even among family members who have migrated.[22]

But how might a culture of mistrust influence teacher truancy at the school level? We expect teacher misbehaviour in general to be strongly related to trust levels via cooperation

[20] Alternatively, Nunn and Wantchekon (2011) hypothesise that inherently less trusting ethnic groups may have been more likely to be exposed to the slave trade, and these groups continue to be less trusting today. However, their data allow them to rule out this reverse causation.

[21] See Putnam (2000), Bisin and Verdier (2001), Guiso, Zapienza, and Zingales (2006), and Tabellini (2008).

[22] See Giuliano (2007), Fernandez (2007), Fernandez and Fogli (2009), Algan and Cahuc (2010).

at the school level. As we are unable to test these specific relationships, we speculate on the channels, and thus potential directions, of the effects. In general, trust is correlated to higher levels of cooperation with others due to humans' tendency to behave as reciprocal altruists – that is, to be kind to those expected to be kind.[23] And indeed, studies suggest that higher levels of trust are correlated to greater cooperation. Evidence from a laboratory experimental game run in the US by Anderson, Mellor, and Milyo (2004) demonstrates that greater trust in others leads to more public good contributions. Likewise in a field experiment also run in the US, Coleman (1996) finds that taxpayers' willingness to pay taxes increases when they are told that tax evasion is at a low level in their district. But evidence on the positive impact of trust on cooperation is not limited to developed countries. Fafchamps (1996), Lyon (2000), Murphy (2002), and Vollan (2012) also provide strong support for the effect of trust on cooperation, based on African case studies.

Yet there may not exist such an unambiguous relationship. Features in the community or school system can evolve to compensate for a lack of leadership and cooperation (Khawja (2009)). Thus we might expect that, while trust increases misbehaviour on average, it may have heterogeneous influences across different types of misbehaviour depending on how easily one can monitor these different types. More precisely, if trust is low, superiors may be keen to monitor teachers because they expect teachers to cooperate less and misbehave more frequently. Thus, superiors may manage to discourage misbehaviour that is easily observable (e.g. absenteeism) but are less able to punish misbehaviour that is more difficult to observe either because it occurs within the classroom (e.g. intimidation or bullying of pupils) or because it relates to activities that are typically dissimulated by perpetrators (e.g. sexual harassment of students).

[23] See Trivers (1971) and Axelrod (1984) on the role that reciprocal altruism plays in cooperation.

Regardless of the direction, the existing evidence leads us to believe that the relationship between trust and teacher truancy is strong. We put this speculation to the test in the coming sections.

5.1.2 Slave trade exposure's orthogonality to omitted variables

For the exclusion restriction to be satisfied, we use past levels of trust resulting from slave trade exposure to proxy for today's trust levels instead of relying directly on contemporary trust. Doing so reduces the likelihood that a common omitted variable determines both today's student performance and past levels of trust. However, this is clearly insufficient. In order to ensure that our IV affects student achievement only through its impact on teacher truancy, we control for additional variables at the school and regional levels that could impact test scores while being affected by regional trust. By accounting for other such channels, we increase our confidence that our IV affects test scores only via teacher truancy.

We start by accounting for competing channels at the school level. If we consider teacher truancy to be greatly influenced by mistrust, then it is equally possible that mistrust impacts student truancy which itself affects test scores. Additionally, the degree to which parents and the community participate in school resource provision can be a product of both capability (level of economic development) and trust (willingness to contribute to a public good) which may be impacted by slave trade exposure. It is therefore critical to include these elements in vector $\mathbf{V_s}$.

We then turn to competing channels at the regional level that are included in vector $\mathbf{Z_r}$. Greater exposure to the slave trade has been linked to lower levels of economic development (Nunn (2008)), so it is important to verify that low test scores do not result from generally poor development levels in the hardest hit areas. In the same vein, we must also account

for average regional levels of trust in the schooling system itself, which notably capture individuals' beliefs about the returns to education and their propensity to become involved in educational politics. Finally, ethnic diversity can lead to collective action failures in public goods provision and therefore education. In western Kenya, Miguel and Gugerty (2005) link ethnic heterogeneity to fewer primary school funding allocations and lower quality school facilities stemming from lower levels of contributions at public fundraising events. Yet, there also exists a potentially endogenous relationship between slavery and ethnic fractionalisation, whereby ethnic fractionalisation increases due to slave trading activities (see Whatley and Gillezeau (2011)). Regional ethnic fractionalisation is therefore a crucial channel to control for in our estimation. Further details on the construction of these variables are found in the following section.

The variables included in vector $\mathbf{Z_r}$ are presented in Panel G of Table 1. First, we create a proxy for average wealth at the regional level. To do so, we compute the average response to the following Afrobarometer question: "Over the past year, how often, if ever, have you or anyone in your family gone without: Enough food to eat?". Responses range from 0 (never) to 4 (always) with the average hovering at a low 1.13. Similarly, our measure of average regional trust in the schooling system derives from the Afrobarometer question "How well or badly would you say the current government is handling the following matters, or haven't you heard enough to say: Addressing educational needs?", where interviewees can respond from 1 (very badly) to 4 (very well). On average, faith in the government regarding educational matters is reasonably strong at 2.88. Finally, we compute a standard measure of ethnic fractionalisation by using one minus the Herfindahl index of ethnic group shares in the total population of a given region.[24]

[24]This index captures the probability that two randomly drawn individuals in a given region belong to

5.2 Data on slave trade exposure

We construct our instrument (the intensity of past slave exports) at the regional level. We are unable to work at a lower level, such as the school level, since the SACMEQ database includes no information on ethnicity. More precisely, we construct a dataset which relies heavily on the approach adopted by Nunn and Wantchekon (2011) who compile slavery data at the level of ethnic groups. In their approach, the modern name of an ethnic group in the Afrobarometer survey is related back to an older ethnic classification of George P. Murdock (1959), and then the intensity of slave exports per Murdock ethnic group is assigned based upon historical records. To create measures of the intensity of past slave exports at the regional level, we also make use of the Afrobarometer survey to construct a proxy for ethnic group distribution at the regional level. We use both rounds 3 (collected at roughly the same time as the SACMEQ II) and 4 (collected approximately 5 years after the SACMEQ II) of the Afrobarometer to increase our sample size and ensure that we have at least 100 respondents in each region.

Clearly, we cannot match every Afrobarometer respondent to an ethnic group classified by Murdock (and thus cannot assign a measure of slave exports to them). Those individuals we were unable to include are the following: those who did not know their ethnicity or refused to name it, those who claimed a "National Identity," those who specified an ethnic group that is not part of Murdock's classification, and those who responded "Other" without specifying the ethnic group to which they belong. Proportions of non-exploitable answers for each region are provided by country and region in Table 7. The lower bound for these non-exploitable answers is 0% while the upper bound is 87% in Zanzibar. Despite this variation,

two different ethnic groups.

Table 7 clearly shows that proportions of non-exploitable answers are consistently low, with only a minority of regions possessing high proportions of such responses.

We therefore include all 67 regions in our primary estimations. However, due to Zanzibar's tremendously high proportion of non-exploitable responses combined with the fact that it encompasses a large number of observations (2,514 students or approximately 10% of our sample), we run a robustness check that removes this problematic region. Our results hold with this exclusion.

After matching of ethnicities in the Afrobarometer surveys 3 and 4 to ethnicities in the Murdock classification, we construct a measure of slave trade exposure at the regional level. Nunn and Wantchekon (2011) explore various measures at the ethnic group level: the total number of slaves exported expressed in thousands (the "sum of slave exports" hereafter), the sum of slave exports normalized by historic area, and the sum of slave exports normalized by historic population. We obtain the sum of slave exports at the regional level in two steps: (i) for each ethnic group in a given region, we multiply the sum of slave exports associated with this ethnic group by the population share of this ethnic group in the region; (ii) we then compute the sum of these products. Put differently, the sum of slave exports at the regional level is the sum of slave exports at the ethnicity level in a given region, weighted by the population share at the ethnicity level in this region. Table 8 reports this weighted sum of slave exports per region. This variable shows a large variance across regions (with a standard deviation of 43.67 as reported in Panel G of Table 1) such that regional totals range from zero exports to over 217 (recall that these figures are expressed in thousands). Consistent with Nunn and Wantchekon's findings, this variance is fueled by a region's distance from the coast and, for our sample of countries specifically, proximity to the Indian Ocean.

We do not use normalized measures in our analysis since we rely on regions, not ethnicity, for which we have no information on the exact historic area nor the precise historic population. In the robustness checks, we show that our results hold if we rely on a different variable to allow for a non-linear relationship between teacher truancy and the slave export intensity in the first stage of our IV approach.

5.3 Results

5.3.1 Average effect of teacher truancy

Our IV approach consists of a first stage, which estimates the impact of slave trade exposure on teacher truancy, followed by a second stage introducing the instrumented term for teacher truancy as the key explanatory variable for math or reading scores on standardized tests. Equation (4) specifies the 1-SLS for teacher truancy:

$$M_s = a + b.S_r + \mathbf{X_i'}.\mathbf{c} + \mathbf{U_c'}.\mathbf{d} + \mathbf{W_j'}.\mathbf{e} + \mathbf{V_s'}.\mathbf{f} + \mathbf{Z_r'}.\mathbf{g} + \mathbf{C'}.\mathbf{h} + \epsilon_i, \tag{4}$$

in which S_r, slave trade exposure, enters as an explanatory variable. We include all control vectors $\mathbf{X_i}$ (student), $\mathbf{U_c}$ (class), $\mathbf{W_j}$ (teacher), $\mathbf{V_s}$ (school), and $\mathbf{Z_r}$ (region) as before, along with country fixed effects, $\mathbf{C}$.

First-stage results are found in Panel B of Tables 9 and 10 for mathematics and reading test scores. Controls are introduced step-wise across six columns: first, average teacher truancy and violence at the school level (column 1), followed by student (column 2), class (column 3), teacher (column 4), school (column 5), and region (column 6) controls. Country fixed effects are included in every column. The usual F-statistics, reported in Panel B, confirm that the first-stage relationship in all cases is strong. Also included in Panel B,

Durbin-Wu-Hausman χ^2 tests soundly reject the null hypothesis and confirm the appropriateness of an IV approach.

In each column of both tables, the first-stage results confirm a strongly significant correlation at a 1% level between slave trade exposure at the regional level and teacher truancy at the school level. The sign of this relationship is negative. This demonstrates that a greater degree of exposure, and thus lower trust, leads to less truancy. This outcome supports our hypothesis, in line with the findings of Nunn and Wantchekon (2011), according to which more exposure to slave trade in the past leads to lower trust levels today and therefore greater sanctioning efforts out of fear of limited cooperation. Note that these efforts seem efficient, as we surmised, only when they target misconduct that is easily observable such as teacher truancy. The relationship between slave trade exposure and teacher truancy is indeed negative and significant while the relationship between slave trade exposure and teacher violence, which is more difficult to observe and monitor by superiors, is positive and significant. (Results available upon request.)

We then turn to the 2-SLS in Equation (5):

$$P_{ij} = a + b.\widehat{M_s} + \mathbf{X'_i.c} + \mathbf{U'_c.d} + \mathbf{W'_j.e} + \mathbf{V'_s.f} + \mathbf{Z'_r.g} + \mathbf{C'.h} + \epsilon_i \tag{5}$$

where we introduce the instrumented measure of teacher truancy, $\widehat{M_s}$, from Equation (4) as the key explanatory variable for math or reading test scores on standardized tests, retaining the same vectors of control variables as before.

The 2-SLS estimates appear in Panel A of Tables 9 and 10 for mathematics and reading test scores. The impact of teacher truancy on students' test scores is significant in neither math nor reading. These results are hardly surprising given the near global absence of

significance in our OLS analysis and the fact that 2-SLS variance is always larger than that of OLS. Of more interest is the robustness of the heterogeneous effects of teacher truancy over student characteristics. We thus proceed to an analysis of teacher truancy according to student SES in the following section.

5.3.2 Heterogeneous effects of teacher truancy across student SES

To analyse heterogeneous effects of teacher truancy across student SES, we instrument teacher truancy (M_s) and the interaction between teacher truancy and student home possessions ($M_s^* SES$) with a linear combination of slave trade exposure and the interaction of slave trade exposure with student home possessions. As such, we estimate Equation (6) in the second stage:

$$P_{ij} = a + b.\widehat{M_s} + c.\widehat{M_s^* SES} + \mathbf{X_i'}.\mathbf{d} + \mathbf{U_c'}.\mathbf{e} + \mathbf{W_j'}.\mathbf{f} + \mathbf{V_s'}.\mathbf{g} + \mathbf{Z_r'}.\mathbf{h} + \mathbf{C'}.\mathbf{i} + \epsilon_i \qquad (6)$$

where $\widehat{M_s}$ and $\widehat{M_s^* SES}$ are instrumented by a linear combination of S_r and $SES^* S_r$.

Estimates of Equation (6) are reported in Table 11. The IV results confirm our OLS analysis. The series of Wald tests at the bottom of Table 11 shows the heterogeneous impact of teacher truancy: the negative effect of truancy only exists for those students in the 83rd percentile and above of the socioeconomic distribution for math and in the 77th percentile for reading.

The IV estimates show that only the richest minority of students experience a negative effect from teacher truancy. Though one might initially expect the poorest students to be the most sensitive to changes in schooling inputs, such students face a host of additional poverty-induced constraints such that the presence or absence of a teacher may not make

a substantial change in their learning outcomes. Interestingly, we no longer observe the positive and significant relationship between teacher truancy and educational achievements for students in the lower percentiles. This suggests that the IV approach allows us to treat a reverse causality problem according to which higher performing students discourage teachers from behaving well.

Our 2-SLS results show a substantial negative effect of teacher truancy on student achievement. If we consider the case of a student belonging to the 90th percentile of the home possession distribution, Table 11 shows that an increase in teacher truancy by one standard deviation leads to a decrease in a student's test score by 0.38 standard deviations in math and 0.43 standard deviations in reading. These orders of magnitude are much larger than those found in the OLS analysis. This feature is again consistent with the fact that our OLS results were plagued by a reverse causality problem. Note that among the exhaustive set of educational interventions reviewed by Kremer and Holla (2009) in the context of developing countries, these impacts at the margin obtained from our IV approach fall near the upper bound. Specifically, they are comparable to the input-based interventions of providing supplemental workbooks (0.33 standard deviations in test scores) and teacher- and NGO-implemented learning materials (0.30 standard deviations in test scores). We provide a sensitivity test in the supplemental appendix that aims to ensure that our IV results hold even when the exclusion restriction is partly violated. This supplemental appendix encompasses additional robustness checks as well.

6 Conclusion

We estimate the effect of teacher truancy on student test scores in a sample of primary schools from eight countries in Sub-Saharan Africa. To do so, we compute indicators of the average incidence of teacher truancy at the school level. Our results reveal that teacher truancy has no average effect on test scores. Rather, it is detrimental only to students from households belonging to the uppermost percentiles of the socioeconomic distribution.

We subject this finding to a robustness check based on the historic exposure of ethnic groups to the slave trade. As Nunn and Wantchekon (2011) find that historic exposure of ethnic groups to the slave trade causes significantly lower levels of trust among those groups today, we expect slave export intensity to be a good predictor of teacher truancy. The first stage of the IV approach confirms the significant relationship between slave trade exposure and teacher truancy. The second stage confirms that teacher truancy has no average effect on student achievement. It does, however, have a robust effect at the margin, influencing students from the upper percentiles of the SES distribution negatively.

That teacher tardiness, absenteeism, and skipping classes appear irrelevant for poorer students is not out of line with existing studies on the effects of school inputs in the African context (Glewwe, Kremer, and Moulin (2009), Kuecken and Valfort (2013)). Our results lend further support to the fact that poorer students are marginalized at school. They suggest that it is solely when other constraints related to the inequality of educational opportunities (poor early childhood development, sporadic enrolment due to household income shocks, elitist curriculum biases, and low expectations) have been lifted that the conduct of teachers plays a significant role in determining educational outcomes. Many of these constraints are economic. Put differently, in contrast to policies that target inequities in educational quality

(Santos (2011)), reduction in economic inequality through enhanced academic performance of poorer students will be best achieved by policies that directly target income redistribution rather than education.

These findings are in line with studies that document the positive effects of rewarding teachers for improvements in student testing (Kingdon and Teal (2007), Glewwe, Ilias, Kremer (2010)). Indeed, these studies show that such improvements do not necessarily occur because teachers improve their attendance. For example, Muralidharan and Sundararaman (2011) investigate group and individual performance pay for teachers in rural government schools in Andhra Pradesh. They find that schools receiving incentives improved student performance on end of year examinations due to the fact that the treatment succeeded in motivating teachers to teach better when they were present. However, teachers do not produce this improvement by being present more often: absence rates remain unaffected by the intervention, suggesting that teachers' obedience to basic rules of conduct is not critical for student performance but rather that teachers' effort to make curricula accessible when present has a more substantial impact.

Our findings beg consideration from policy-makers aiming to improve educational quality, particularly for those countries with large proportions of students in the bottom of the socioeconomic distribution. However, our results are only a first step toward constructing a more holistic understanding of how teacher attendance is consequential for learning outcomes. Further exploration of the conditions under which attendance could make a difference for all students, not just a minority, constitutes an important avenue for future research.

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7 Graphs and Tables

Table 1: Summary statistics

	Mean	Standard Deviation	Observations
Panel A: Dependent variables			
Math test scores	489.89	92.26	27,583
Reading test scores	490.62	93.32	27,800
Panel B: Student characteristics			
Student sex (female)	0.48	0.50	27,796
Student age	14.22	1.84	27,800
Student home possessions	0.33	0.22	27,800
Student has access to a textbook in math	0.86	0.35	27,800
Student has access to a textbook in reading	0.88	0.32	27,800
Panel C: Class characteristics			
Class size	42.83	14.37	3,918
Class girl ratio	0.10	0.10	3,917
Panel D: Math teacher characteristics			
Math teacher sex (female)	0.42	0.49	2,201
Math teacher age	34.92	7.73	2,234
Math teacher qualification (primary)	0.07	0.25	2,234
Math teacher qualification (junior secondary)	0.23	0.42	2,234
Math teacher qualification (senior secondary)	0.56	0.50	2,234
Math teacher qualification (A-level/tertiary)	0.14	0.34	2,234
Math teacher test score	25.79	7.05	2,183
Math teacher average resources	0.59	0.26	2,214
Panel E: Reading teacher characteristics			
Reading teacher sex (female)	0.49	0.50	2,264
Reading teacher age	34.69	7.77	2,296
Reading teacher qualification (primary)	0.08	0.27	2,296
Reading teacher qualification (junior secondary)	0.23	0.42	2,296
Reading teacher qualification (senior secondary)	0.53	0.50	2,296
Reading teacher qualification (A-level/tertiary)	0.16	0.37	2,296
Reading teacher test score	30.60	5.82	2,279
Reading teacher average resources	0.59	0.26	2,280

	Mean	Standard Deviation	Observations
Panel F: School characteristics			
Average teacher truancy	1.76	0.44	1,590
Average teacher violence	1.27	0.40	1,590
Director sex (female)	0.21	0.40	1,587
Director age	44.37	7.33	1,589
Director qualification (primary)	0.07	0.25	1,590
Director qualification (junior secondary)	0.16	0.37	1,590
Director qualification (senior secondary)	0.52	0.50	1,590
Director qualification (A-level/tertiary)	0.26	0.44	1,590
Director experience	20.91	7.69	1,590
School location (urban)	0.40	0.49	1,590
School condition (good/minor repair)	0.51	0.50	1,590
School resources	0.35	0.20	1,590
Student misbehaviour (own grades)	1.72	0.34	1,590
Student misbehaviour (peers' grades)	1.75	0.45	1,590
Community involvement	0.34	0.22	1,590
Average math test score	488.27	69.34	1,603
Average reading test score	488.59	70.14	1,603
Panel G: Regional characteristics			
Sum of slave exports (in thousands)	15.71	43.67	67
Regional wealth	1.13	0.28	67
Regional trust in schools	2.88	0.30	67
Ethnic fractionalisation	0.60	0.26	67

Notes: Our data include 27,800 students, 3,918 classes, 2,296 reading teachers, 2,234 math teachers, 1,603 schools and 67 regions.

Table 2: Breakdown of teacher truancy

	Mean	Standard Deviation	Observations
Tardiness	2.03	0.46	1,590
Absenteeism	1.74	0.61	1,590
Skipping class	1.51	0.61	1,590
Average truancy	1.76	0.44	1,590

Notes: Average truancy is an arithmetic average of tardiness, absenteeism and skipping class.

Table 3: Correlation between types of teacher misbehaviour

	Average truancy	Average violence
Average truancy	1	
Average violence	0.5289***	1

Notes: Average truancy is an arithmetic average of tardiness, absenteeism and skipping class. Average violence is an arithmetic average of student bullying, sexual harassment, and abusive language. *, ** and *** indicate significance at the 10, 5 and 1% levels.

Table 4: Average teacher truancy and math scores: OLS results

	Dep. var.: Math scores				
	(1)	(2)	(3)	(4)	(5)
Average truancy	-8.885** (4.200)	-8.140** (3.924)	-7.604* (3.907)	-6.524* (3.707)	0.143 (0.305)
Average violence	4.284 (4.503)	2.971 (4.316)	2.755 (4.302)	1.203 (4.345)	-0.863*** (0.331)
Student sex (female)		-15.220*** (1.101)	-15.473*** (1.057)	-14.674*** (1.095)	-12.702*** (0.942)
Student age		-5.654*** (0.421)	-5.801*** (0.425)	-5.626*** (0.420)	-3.991*** (0.264)
Student home possession		59.635*** (5.137)	61.061*** (5.245)	57.024*** (4.822)	13.711*** (2.009)
Student has access to a textbook in math		8.657*** (2.995)	8.274*** (2.979)	10.872*** (2.712)	4.925*** (1.094)
Class size			-0.149 (0.091)	-0.164* (0.092)	0.008 (0.015)
Class girl ratio			12.591 (13.827)	5.847 (13.367)	9.790*** (1.814)
Math teacher sex (female)				4.858** (2.267)	-0.315 (0.529)
Math teacher age				0.240* (0.143)	-0.005 (0.029)
Math teacher qualification (junior secondary)				5.771 (3.991)	0.182 (1.207)
Math teacher qualification (senior secondary)				3.015 (3.590)	-0.323 (1.135)
Math teacher qualification (A-level/Tertiary)				13.767*** (4.854)	-0.021 (1.212)
Math teacher test score				1.059*** (0.223)	-0.032 (0.035)
Math teacher average resources				12.629** (5.235)	-1.208 (0.858)
Student misbehaviour (own grades)					1.326*** (0.425)
Student misbehaviour (peers' grades)					-0.187 (0.288)
Community involvement					0.512 (0.627)
School condition					0.160 (0.212)
School resources					-6.547*** (1.007)
School location					-1.977*** (0.318)
Director sex (female)					-0.396 (0.275)
Director age					-0.002 (0.030)
Director qualification (junior secondary)					-0.381 (0.439)
Director qualification (senior secondary)					-0.778* (0.449)
Director qualification (A-level/Tertiary)					-0.810* (0.483)
Director experience					-0.024 (0.028)
School math score					0.980*** (0.003)
Student characteristics	no	yes	yes	yes	yes
Classroom characteristics	no	no	yes	yes	yes
Teacher characteristics	no	no	no	yes	yes
Other school characteristics	no	no	no	no	yes
Regional fixed effects	yes	yes	yes	yes	yes
R^2	0.304	0.340	0.340	0.362	0.565
Observations	27,360	27,356	27,340	25,396	25,351

Notes: This table reports OLS estimates for math scores. The unit of observation is the student. The first column controls for average teacher truancy and violence as well as regional fixed effects. The second column adds student characteristics, followed by classroom characteristics (column 3), teacher characteristics (column 4), and other school characteristics (column 5). Standard errors are between parentheses and clustered at the school level. *, ** and *** indicate significance at the 10, 5 and 1% levels.

Table 5: Average teacher truancy and reading scores: OLS results

	Dep. var.: Reading scores				
	(1)	(2)	(3)	(4)	(5)
Average truancy	-9.733** (4.280)	-9.348** (3.771)	-8.996** (3.763)	-7.306** (3.685)	-0.215 (0.373)
Average violence	7.438* (4.392)	6.273 (3.986)	6.154 (3.977)	5.346 (3.980)	-0.436 (0.402)
Student sex (female)		-3.427*** (1.051)	-3.677*** (1.009)	-4.033*** (1.021)	-2.358*** (0.897)
Student age		-7.352*** (0.441)	-7.455*** (0.446)	-6.994*** (0.437)	-4.833*** (0.260)
Student home possession		81.504*** (5.081)	82.549*** (5.208)	75.592*** (4.872)	18.376*** (2.153)
Student has access to a textbook in reading		16.361*** (2.558)	16.183*** (2.552)	16.322*** (2.590)	9.549*** (1.266)
Class size			-0.077 (0.093)	-0.113 (0.094)	-0.027 (0.017)
Class girl ratio			13.505 (14.105)	12.502 (13.801)	3.797* (2.017)
Reading teacher sex (female)				10.622*** (2.337)	-1.306** (0.523)
Reading teacher age				0.189 (0.148)	-0.035 (0.030)
Reading teacher qualification (junior secondary)				4.406 (4.183)	0.198 (0.873)
Reading teacher qualification (senior secondary)				2.983 (4.023)	-0.120 (0.911)
Reading teacher qualification (A-level/Tertiary)				15.666*** (5.084)	0.239 (1.029)
Reading teacher test score				1.325*** (0.222)	0.047 (0.041)
Reading teacher average resources				16.074*** (4.906)	-1.704* (0.873)
Student misbehaviour (own grades)					1.340** (0.541)
Student misbehaviour (peers' grades)					-0.313 (0.358)
Community involvement					1.131 (0.749)
School condition					0.393 (0.248)
School resources					-8.775*** (1.182)
School location					-2.642*** (0.347)
Director sex (female)					-0.617* (0.319)
Director age					-0.028 (0.034)
Director qualification (junior secondary)					-0.298 (0.522)
Director qualification (senior secondary)					-1.424*** (0.524)
Director qualification (A-level/Tertiary)					-1.272** (0.559)
Director experience					-0.020 (0.032)
School reading score					0.971*** (0.004)
Student characteristics	no	yes	yes	yes	yes
Classroom characteristics	no	no	yes	yes	yes
Teacher characteristics	no	no	no	yes	yes
Other school characteristics	no	no	no	no	yes
Regional fixed effects	yes	yes	yes	yes	yes
R^2	0.291	0.348	0.348	0.359	0.568
Observations	27,575	27,571	27,555	26,595	26,541

Notes: This table reports OLS estimates for reading scores. The unit of observation is the student. The first column controls for average teacher truancy and violence as well as regional fixed effects. The second column adds student characteristics, followed by classroom characteristics (column 3), teacher characteristics (column 4), and other school characteristics (column 5). Standard errors are between parentheses and clustered at the school level. *, ** and *** indicate significance at the 10, 5 and 1% levels.

Table 6: Average teacher truancy and math and reading scores, depending on the position of the student in the SES distribution: OLS results

	Dep. var.: Test scores	
	Math	Reading
	(1)	(2)
Average truancy	2.987**	2.694*
	(1.265)	(1.382)
Average truancy*Home possession	-8.429**	-8.702**
	(3.666)	(3.945)
$\alpha_{M_s} + 0(\beta_{M_s^* SES}) = 0$	0.02	0.05
$\alpha_{M_s} + 0.07(\beta_{M_s^* SES}) = 0$	0.02	0.06
$\alpha_{M_s} + 0.14(\beta_{M_s^* SES}) = 0$	0.02	0.09
$\alpha_{M_s} + 0.21(\beta_{M_s^* SES}) = 0$	0.03	0.18
$\alpha_{M_s} + 0.29(\beta_{M_s^* SES}) = 0$	0.11	0.63
$\alpha_{M_s} + 0.36(\beta_{M_s^* SES}) = 0$	0.94	0.28
$\alpha_{M_s} + 0.43(\beta_{M_s^* SES}) = 0$	0.18	0.05
$\alpha_{M_s} + 0.50(\beta_{M_s^* SES}) = 0$	0.07	0.03
$\alpha_{M_s} + 0.57(\beta_{M_s^* SES}) = 0$	0.05	0.02
$\alpha_{M_s} + 0.64(\beta_{M_s^* SES}) = 0$	0.04	0.02
$\alpha_{M_s} + 0.71(\beta_{M_s^* SES}) = 0$	0.03	0.02
$\alpha_{M_s} + 0.79(\beta_{M_s^* SES}) = 0$	0.03	0.02
$\alpha_{M_s} + 0.86(\beta_{M_s^* SES}) = 0$	0.03	0.02
$\alpha_{M_s} + 0.93(\beta_{M_s^* SES}) = 0$	0.03	0.02
$\alpha_{M_s} + 1(\beta_{M_s^* SES}) = 0$	0.03	0.02
Student characteristics	yes	yes
Classroom characteristics	yes	yes
Teacher characteristics	yes	yes
Other school characteristics	yes	yes
Regional fixed effects	yes	yes
R^2	0.565	0.568
Observations	25,351	26,541

Notes: This table reports OLS estimates for math (column 1) and reading (column 2) scores. The unit of observation is the student. We control in both columns for student, classroom, teacher and other school characteristics, as well as for regional fixed effects. The lower panel reports the Wald test p-value for $\alpha_{M_s} + x\beta_{M_s^* SES}$, where α_{M_s} is the coefficient of M_s, x is the home possession level corresponding to a given percentile, and $\beta_{M_s^* SES}$ is the coefficient of $M_s^* SES$. Standard errors are between parentheses and clustered at the school level. *, ** and *** indicate significance at the 10, 5 and 1% levels.

Table 7: Proportion of non-exploitable responses by country and region

Country	Region	Non-exploitable responses (%)	Country	Region	Non-exploitable responses (%)
Botswana	Northern	0	Namibia	Khomas	21
Botswana	Central North	0	Namibia	Kunene	0
Botswana	Central South	0	Namibia	Ohangwena	0
Botswana	South Central	0	Namibia	Omaheke	19
Botswana	Gaborone	0	Namibia	Omusati	0
Botswana	Southern	0	Namibia	Oshana	0
Botswana	Western	0	Namibia	Oshikoto	0
Kenya	Nairobi	0	Namibia	Otjozondjupa	0
Kenya	Central	0	Tanzania	Central	16
Kenya	Eastern	0	Tanzania	Northern	67
Kenya	Rift Valley	0	Tanzania	Kilimanjaro	8
Kenya	Nyanza	0	Tanzania	North East	54
Kenya	Western	0	Tanzania	Eastern	49
Kenya	North Eastern	0	Tanzania	Southern	62
Kenya	Coast	4	Tanzania	Southern Highland	54
Malawi	Central	0	Tanzania	Western	2
Malawi	North	0	Tanzania	South Western	50
Malawi	South	0	Tanzania	Kagera	28
Mozambique	Maputo	0	Tanzania	Mwanza	12
Mozambique	Maputo City	2	Tanzania	Zanzibar	87
Mozambique	Gaza	0	Uganda	Central	2
Mozambique	Inhambane	0	Uganda	West	1
Mozambique	Sofala	2	Uganda	North	1
Mozambique	Tete	34	Uganda	East	0
Mozambique	Manica	2	Zambia	Lusaka	0
Mozambique	Zambezia	5	Zambia	Central	0
Mozambique	Nampula	3	Zambia	Copperbelt	1
Mozambique	Niassa	1	Zambia	Eastern	0
Mozambique	Cabo Delgado	0	Zambia	Luapula	1
Namibia	Caprivi	0	Zambia	Northern	1
Namibia	Erongo	12	Zambia	North Western	0
Namibia	Hardap	52	Zambia	Southern	0
Namibia	Karas	22	Zambia	Western	0
Namibia	Kavango	0			

Table 8: The weighted sum of slave exports by country and region (in thousands)

Country	Region	Sum of slave exports	Country	Region	Sum of slave exports
Botswana	Northern	0.0330683	Namibia	Khomas	0.2171106
Botswana	Central North	0.3468865	Namibia	Kunene	0
Botswana	Central South	0.1425097	Namibia	Ohangwena	0.4027707
Botswana	South Central	0.0154725	Namibia	Omaheke	0
Botswana	Gaborone	0.0154725	Namibia	Omusati	0
Botswana	Southern	0.0142496	Namibia	Oshana	0.4245957
Botswana	Western	0.0120249	Namibia	Oshikoto	0
Kenya	Nairobi	0.5965503	Namibia	Otjozondjupa	0
Kenya	Central	0.2374288	Tanzania	Central	3.827547
Kenya	Eastern	1.511454	Tanzania	Northern	0.4878297
Kenya	Rift Valley	0.2078156	Tanzania	Kilimanjaro	1.744673
Kenya	Nyanza	0.2828181	Tanzania	North East	6.621765
Kenya	Western	0.7312449	Tanzania	Eastern	4.442257
Kenya	North Eastern	0.0861513	Tanzania	Southern	4.464863
Kenya	Coast	0.8610657	Tanzania	Southern Highland	3.717456
Malawi	Central	18.02095	Tanzania	Western	16.74734
Malawi	North	10.84065	Tanzania	South Western	4.450484
Malawi	South	62.27419	Tanzania	Kagera	1.049425
Mozambique	Maputo	3.662392	Tanzania	Mwanza	5.336149
Mozambique	Maputo City	6.680215	Tanzania	Zanzibar	2.332902
Mozambique	Gaza	3.640092	Uganda	Central	3.18477
Mozambique	Inhambane	9.960493	Uganda	West	0.5609632
Mozambique	Sofala	57.54734	Uganda	North	0.2628781
Mozambique	Tete	37.78462	Uganda	East	0.2262252
Mozambique	Manica	34.34928	Zambia	Lusaka	5.954599
Mozambique	Zambezia	133.1877	Zambia	Central	3.995893
Mozambique	Nampula	217.1981	Zambia	Copperbelt	3.568301
Mozambique	Niassa	194.6384	Zambia	Eastern	5.780111
Mozambique	Cabo Delgado	169.0886	Zambia	Luapula	2.78514
Namibia	Caprivi	0	Zambia	Northern	3.190974
Namibia	Erongo	0	Zambia	North Western	1.730383
Namibia	Hardap	0	Zambia	Southern	0.4074457
Namibia	Karas	0	Zambia	Western	0.1741409
Namibia	Kavango	0.442015			

Table 9: Average teacher truancy and math scores: IV results

	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: 2-SLS - Dep. var.: Math test scores					
Average truancy	182.271***	41.773	18.033	1.899	-11.676	-15.204
	(49.076)	(34.110)	(28.998)	(25.833)	(22.883)	(31.459)
Student characteristics	no	yes	yes	yes	yes	yes
Classroom characteristics	no	no	yes	yes	yes	yes
Teacher characteristics	no	no	no	yes	yes	yes
Other school characteristics	no	no	no	no	yes	yes
Regional characteristics	no	no	no	no	no	yes
Country fixed effects	yes	yes	yes	yes	yes	yes
R^2	.	0.253	0.285	0.331	0.563	0.561
Observations	27,360	27,356	27,340	25,396	25,351	25,351
	Panel B: 1-SLS - Dep. var.: Teacher Misbehaviour					
Slave trade exposure	-0.0004***	-0.0004***	-0.0005***	-0.0005***	-0.0005***	-0.0004***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Student characteristics	no	yes	yes	yes	yes	yes
Classroom characteristics	no	no	yes	yes	yes	yes
Teacher characteristics	no	no	no	yes	yes	yes
School characteristics	no	no	no	no	yes	yes
Regional characteristics	no	no	no	no	no	yes
Country fixed effects	yes	yes	yes	yes	yes	yes
F-statistic	28.175***	31.301***	41.091***	53.091***	56.701***	29.453***
DWH χ^2						42.97***
R^2	0.299	0.300	0.304	0.312	0.417	0.420
Observations	27,360	27,356	27,340	25,396	25,351	25,351

Notes: The table reports IV estimates for math test scores. The unit of observation is the student. The first column controls for average teacher truancy and violence as well as country fixed effects. The second column adds student characteristics, followed by classroom characteristics (column 3), teacher characteristics (column 4), other school characteristics (column 5), and region characteristics (column 6). Robust standard errors are in parentheses. *, ** and *** indicate significance at the 10, 5 and 1% levels.

Table 10: Average teacher truancy and reading scores: IV results

	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: 2-SLS - Dep. var.: Reading test scores					
Average truancy	218.551***	-1.884	-15.677	-47.312	-34.360	-41.846
	(58.549)	(38.386)	(33.645)	(29.026)	(40.058)	(30.336)
Student characteristics	no	yes	yes	yes	yes	yes
Classroom characteristics	no	no	yes	yes	yes	yes
Teacher characteristics	no	no	no	yes	yes	yes
Other school characteristics	no	no	no	no	yes	yes
Regional characteristics	no	no	no	no	no	yes
Country fixed effects	yes	yes	yes	yes	yes	yes
R^2	.	0.270	0.270	0.280	0.297	0.545
Observations	27,575	27,571	27,555	26,595	26,541	26,541
	Panel B: 1-SLS - Dep. var.: Teacher Misbehaviour					
Slave trade exposure	-0.0004***	-0.0004***	-0.0005***	-0.0005***	-0.0004***	-0.0004***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Student characteristics	no	yes	yes	yes	yes	yes
Classroom characteristics	no	no	yes	yes	yes	yes
Teacher characteristics	no	no	no	yes	yes	yes
Other school characteristics	no	no	no	no	yes	yes
Regional characteristics	no	no	no	no	no	yes
Country fixed effects	yes	yes	yes	yes	yes	yes
F-statistic	28.788***	31.823***	41.488***	56.012***	30.560***	40.656***
DWH χ^2						18.32***
R^2	0.300	0.300	0.303	0.317	0.322	0.424
Observations	27,575	27,571	27,555	26,595	26,541	26,541

Notes: The table reports IV estimates for reading test scores. The unit of observation is the student. The first column controls for average teacher truancy and violence as well as country fixed effects. The second column adds student characteristics, followed by classroom characteristics (column 3), teacher characteristics (column 4), other school characteristics (column 5), and region characteristics (column 6). Robust standard errors are in parentheses. *, ** and *** indicate significance at the 10, 5 and 1% levels.

Table 11: Average teacher truancy and test scores according to student SES: 2-SLS results

	Dep. var.: Test scores	
	Math	Reading
	(1)	(2)
Average truancy	135.222	50.600
	(100.583)	(93.493)
Average truancy*Home possession	-335.789**	-220.708
	(161.719)	(170.084)
$\alpha_{M_s} + 0(\beta_{M_s^* SES}) = 0$	0.18	0.59
$\alpha_{M_s} + 0.07(\beta_{M_s^* SES}) = 0$	0.21	0.67
$\alpha_{M_s} + 0.14(\beta_{M_s^* SES}) = 0$	0.27	0.79
$\alpha_{M_s} + 0.21(\beta_{M_s^* SES}) = 0$	0.35	0.96
$\alpha_{M_s} + 0.29(\beta_{M_s^* SES}) = 0$	0.49	0.80
$\alpha_{M_s} + 0.36(\beta_{M_s^* SES}) = 0$	0.74	0.46
$\alpha_{M_s} + 0.43(\beta_{M_s^* SES}) = 0$	0.82	0.14
$\alpha_{M_s} + 0.50(\beta_{M_s^* SES}) = 0$	0.27	0.01
$\alpha_{M_s} + 0.57(\beta_{M_s^* SES}) = 0$	0.02	0.002
$\alpha_{M_s} + 0.64(\beta_{M_s^* SES}) = 0$	0.002	0.002
$\alpha_{M_s} + 0.71(\beta_{M_s^* SES}) = 0$	0.001	0.01
$\alpha_{M_s} + 0.79(\beta_{M_s^* SES}) = 0$	0.001	0.01
$\alpha_{M_s} + 0.86(\beta_{M_s^* SES}) = 0$	0.002	0.02
$\alpha_{M_s} + 0.93(\beta_{M_s^* SES}) = 0$	0.002	0.03
$\alpha_{M_s} + 1(\beta_{M_s^* SES}) = 0$	0.004	0.04
Student characteristics	yes	yes
Classroom characteristics	yes	yes
Teacher characteristics	yes	yes
Other school characteristics	yes	yes
Regional fixed effects	yes	yes
R^2	0.464	0.524
Observations	25,351	26,541

Notes: This table reports 2-SLS estimates for average teacher truancy. The unit of observation is the student. We control in both columns for student, classroom, teacher and other school characteristics, as well as for country fixed effects. The lower panel reports the Wald test p-value for $\alpha_{M_s} + x\beta_{M_s^* SES}$, where α_{M_s} is the coefficient of M_s, x is the home possession level corresponding to a given percentile, and $\beta_{M_s^* SES}$ is the coefficient of $M_s^* SES$. Robust standard errors are in parentheses. *, ** and *** indicate significance at the 10, 5 and 1% levels.

Supplementary appendix (not for publication)
Economic inequality, teacher truancy and learning: Evidence from Sub-Saharan Africa

Contents

1 IV sensitivity test

A lack of additional suitable instruments for teacher truancy means that our IV results strongly depend on the assumption that the exclusion restriction is valid. More precisely, consider the reduced form model $P_{ij} = \alpha + \beta M_s + \gamma M_s * SES + \delta S_r + \eta S_r * SES + \zeta SES + \epsilon$ where, as before, M_s is the endogenous teacher truancy and S_r is the exogenous instrument. We assume that $\delta = 0$ (and therefore that $\eta = 0$). When δ is non-zero, the exclusion restriction is violated, and we expect that our results no longer hold. On the other hand, a violation of the exclusion restriction may not pose a problem to the validity of our results. Conley, Hansen, and Rossi (2012) propose sensitivity tests that allow δ to deviate from zero. In other words, we are able to test the robustness of our results to a relaxation of the exclusion restriction. To do so, we rely on two sensitivity tests: the union of confidence intervals approach (UCI) and the local-to-zero approximation (LTZ).

The UCI approach operates under the premise that estimates of β and γ can be obtained conditional on any potential values of δ. Setting a support assumption on δ provides conservative interval estimates for β and γ. It does not require the specification of a full prior but rather a calibration using a range of plausible values. To obtain plausible values for δ, we proceed in two steps. We first regress student scores on slave trade exports, students SES, the interaction between slave trade exports and SES, and country fixed effects. We then calibrate δ based on the 95% confidence interval associated to the coefficient of slave trade exports obtained from the first step.

The local-to-zero approximation considers δ to be random and requires the specification of a prior. In this case, the value of δ is drawn from a large sample in which we assume that prior uncertainty about the violation of the exclusion restriction is the same as sampling uncertainty. We program our prior with the point estimate and variance resulting from the same simple estimation as with the UCI test.

Results for these tests are presented in Table 12, alongside the original point estimates and 95% confidence intervals associated to our results in Section 5.3.2 (see Table 11). The UCI test produces a confidence interval only, while the LTZ test produces both a point estimate and confidence interval. Depending on the prior assumptions for each test, the resulting confidence intervals may be wide. To be sure, the test results for both UCI and LTZ do not coincide precisely with the original estimates. However, they indicate that, even with a violation of the exclusion restriction, our result according to which teacher truancy is detrimental only to children of the uppermost percentiles holds. The point estimate of the interaction between teacher truancy and SES is indeed negative and large compared to the positive point estimate of teacher truancy (non-interacted). These outcomes increase our confidence that our original estimates for the instrumented truancy are plausible even if our instrument violates the exclusion restriction.

Table 12: Average teacher truancy and test scores according to student SES: IV sensitivity tests

		Dep. var.: Test scores			
		Math		Reading	
		(1)		(2)	
Average truancy	Original	135.222	[-62, 332]	50.600	[-133, 234]
	UCI	.	[155, 2454]	.	[208, 2206]
	LTZ	1040.294	[709, 1372]	996.522	[683, 1310]
Average truancy*Home possession	Original	-335.789	[-653, -19]	-220.708	[-554, 113]
	UCI	.	[-3706, -236]	.	[-3545, -260]
	LTZ	-1579.891	[-2065, -1095]	-1560.152	[-2050, -1070]

Notes: This table reports original 2-SLS point estimates and 95% confidence intervals for average teacher truancy and average teacher truancy interacted with student SES. It also reports confidence intervals for the UCI test and point estimates and confidence intervals for the LTZ test.

2 Additional robustness checks

We test the robustness of the two main results from the previous section: (i) slave trade exposure is significantly correlated with average teacher truancy even after the inclusion of all controls at the student, class, teacher, school, region, and country levels; (ii) the negative impact of average teacher truancy is significant only for the uppermost percentiles of the SES distribution. Our results are consistent throughout these checks.

2.1 Alternative slave export measure

We test the reliability of our two main results by replacing our original slave trade exposure measure with the weighted average of the natural logarithm of one plus the sum of slave exports at the ethnicity level in a given region. Table 13 reports 1-SLS estimates that describe the relationship between this alternative measure and teacher truancy after controlling for all other explanatory variables. We observe a negative and significant relationship (at the 1% level) between both variables for math and reading. These results are entirely consistent with our original first-stage results.

The 1-SLS results are followed by Table 14 which presents 2-SLS estimates resulting from Equation (6). We find that the impact of average teacher truancy is negative and significant for students belonging to the 91st percentile and above in both math and reading. Again, this is in line with our finding that teacher truancy negatively impacts wealthier students only.

2.1.1 1-SLS results

Table 13: Average teacher truancy and the log of slave exports: 1-SLS results

	Dep. var.: Average truancy	
	Math	Reading
	(1)	(2)
Log of slave exports	-0.005***	-0.005***
	0.002	0.002
Student characteristics	yes	yes
Classroom characteristics	yes	yes
Teacher characteristics	yes	yes
Other school characteristics	yes	yes
Regional characteristics	yes	yes
Country fixed effects	yes	yes
F-statistic	11.393***	9.552***
DWH χ^2	59.47***	40.07***
R^2	0.419	0.423
Observations	25,351	26,541

Notes: This table reports 1-SLS estimates for average teacher truancy. The unit of observation is the student. We control in both columns for student, classroom, teacher, other school, and regional characteristics, as well as for country fixed effects. Robust standard errors are between parentheses. *, ** and *** indicate significance at the 10, 5 and 1% levels.

2.1.2 2-SLS results

Table 14: Average teacher truancy and test scores according to student SES with the log of slave exports as an instrument: 2-SLS results

	Dep. var.: Test scores	
	Math	Reading
	(1)	(2)
Average truancy	168.377	79.008
	(224.730)	(234.278)
Average truancy*Home possession	-318.462	-202.394
	(303.377)	(326.978)
$\alpha_{M_s} + 0(\beta_{M_s^* SES}) = 0$	0.45	0.74
$\alpha_{M_s} + 0.07(\beta_{M_s^* SES}) = 0$	0.47	0.76
$\alpha_{M_s} + 0.14(\beta_{M_s^* SES}) = 0$	0.50	0.79
$\alpha_{M_s} + 0.21(\beta_{M_s^* SES}) = 0$	0.53	0.83
$\alpha_{M_s} + 0.29(\beta_{M_s^* SES}) = 0$	0.58	0.88
$\alpha_{M_s} + 0.36(\beta_{M_s^* SES}) = 0$	0.64	0.96
$\alpha_{M_s} + 0.43(\beta_{M_s^* SES}) = 0$	0.74	0.94
$\alpha_{M_s} + 0.50(\beta_{M_s^* SES}) = 0$	0.91	0.77
$\alpha_{M_s} + 0.57(\beta_{M_s^* SES}) = 0$	0.81	0.49
$\alpha_{M_s} + 0.64(\beta_{M_s^* SES}) = 0$	0.36	0.15
$\alpha_{M_s} + 0.71(\beta_{M_s^* SES}) = 0$	0.04	0.02
$\alpha_{M_s} + 0.79(\beta_{M_s^* SES}) = 0$	0.02	0.02
$\alpha_{M_s} + 0.86(\beta_{M_s^* SES}) = 0$	0.03	0.09
$\alpha_{M_s} + 0.93(\beta_{M_s^* SES}) = 0$	0.05	0.15
$\alpha_{M_s} + 1(\beta_{M_s^* SES}) = 0$	0.08	0.21
Student characteristics	yes	yes
Classroom characteristics	yes	yes
Teacher characteristics	yes	yes
Other school characteristics	yes	yes
Regional fixed effects	yes	yes
R^2	0.430	0.534
Observations	25,351	26,541

Notes: This table reports 2-SLS estimates for average teacher truancy. The unit of observation is the student. We control in both columns for student, classroom, teacher and other school characteristics, as well as for country fixed effects. The lower panel reports the Wald test p-value for $\alpha_{M_s} + x\beta_{M_s^* SES}$, where α_{M_s} is the coefficient of M_s, x is the home possession level corresponding to a given percentile, and $\beta_{M_s^* SES}$ is the coefficient of $M_s^* SES$. Robust standard errors are in parentheses. *, ** and *** indicate significance at the 10, 5 and 1% levels.

2.2 Restrictions in the coding process

As described in the data section, we test all 67 SACMEQ regions despite the fact that Zanzibar is problematic due to its high proportion of non-exploitable answers with respect to the ethnicity question (87%) as well as its large weight in our sample (roughly 10%). It is therefore critical to test whether our two main results hold when Zanzibar is removed. First, in Table 15, we report 1-SLS estimates of the relationship between our slave trade exposure measure and average teacher truancy. In support of our first finding, we observe that the coefficient of slave trade exposure remains negative and significant the 1% level for truancy.

In Table 16, we present 2-SLS results concerning our second assertion – that teacher truancy matters only for the uppermost levels of SES. These estimates stem from Equation (6) as before. The second-stage results hold such that the impact of average teacher truancy is still negative and significant for wealthier students: in math from the 83rd percentile and up, in reading, from the 77th percentile and up. This check confirms the robustness of our results to the removal of our least reliable regional data.

2.2.1 1-SLS results

Table 15: Average teacher truancy and slave trade exposure with reduced sample: 1-SLS results

	Dep. var.: Average truancy	
	Math	Reading
	(1)	(2)
Slave trade exposure	-0.0004***	-0.0004***
	(0.000)	(0.000)
Student characteristics	yes	yes
Classroom characteristics	yes	yes
Teacher characteristics	yes	yes
Other school characteristics	yes	yes
Regional fixed effects	yes	yes
F-statistic	34.5288***	46.5888***
DWH χ^2	74.17***	17.90***
R^2	0.434	0.439
Observations	25,351	26,541

Notes: This table reports 1-SLS estimates for average teacher truancy. The unit of observation is the student. We control in both columns for student, classroom, teacher, other school, and regional characteristics, as well as for country fixed effects. Robust standard errors are in parentheses. *, ** and *** indicate significance at the 10, 5 and 1% levels.

2.2.2 2-SLS results

Table 16: Average teacher truancy and test scores according to student SES with reduced sample: 2-SLS results

	Dep. var.: Test scores	
	Math	Reading
	(1)	(2))
Average truancy	126.810	52.765
	(85.324)	(82.483)
Average truancy*Home possession	-323.135**	-224.564
	(137.234)	(148.049)
$\alpha_{M_s} + 0(\beta_{M_s^* SES}) = 0$	0.14	0.52
$\alpha_{M_s} + 0.07(\beta_{M_s^* SES}) = 0$	0.17	0.61
$\alpha_{M_s} + 0.14(\beta_{M_s^* SES}) = 0$	0.23	0.74
$\alpha_{M_s} + 0.21(\beta_{M_s^* SES}) = 0$	0.32	0.93
$\alpha_{M_s} + 0.29(\beta_{M_s^* SES}) = 0$	0.48	0.80
$\alpha_{M_s} + 0.36(\beta_{M_s^* SES}) = 0$	0.78	0.44
$\alpha_{M_s} + 0.43(\beta_{M_s^* SES}) = 0$	0.73	0.12
$\alpha_{M_s} + 0.50(\beta_{M_s^* SES}) = 0$	0.21	0.01
$\alpha_{M_s} + 0.57(\beta_{M_s^* SES}) = 0$	0.02	0.002
$\alpha_{M_s} + 0.64(\beta_{M_s^* SES}) = 0$	0.002	0.001
$\alpha_{M_s} + 0.71(\beta_{M_s^* SES}) = 0$	0.000	0.003
$\alpha_{M_s} + 0.79(\beta_{M_s^* SES}) = 0$	0.000	0.01
$\alpha_{M_s} + 0.86(\beta_{M_s^* SES}) = 0$	0.001	0.01
$\alpha_{M_s} + 0.93(\beta_{M_s^* SES}) = 0$	0.001	0.01
$\alpha_{M_s} + 1(\beta_{M_s^* SES}) = 0$	0.001	0.02
Student characteristics	yes	yes
Classroom characteristics	yes	yes
Teacher characteristics	yes	yes
Other school characteristics	yes	yes
Regional fixed effects	yes	yes
R^2	0.485	0.536
Observations	23,248	24,277

Notes: This table reports 2-SLS estimates for average teacher truancy. The unit of observation is the student. We control in both columns for student, classroom, teacher and other school characteristics, as well as for country fixed effects. The lower panel reports the Wald test p-value for $\alpha_{M_s} + x\beta_{M_s^* SES}$, where α_{M_s} is the coefficient of M_s, x is the home possession level corresponding to a given percentile, and $\beta_{M_s^* SES}$ is the coefficient of $M_s^* SES$. Robust standard errors are in parentheses. *, ** and *** indicate significance at the 10, 5 and 1% levels.

2.3 Alternative measure of truancy

Our decision to use an average of three variables for truancy could be called into question if doing so exacerbates measurement issues from our already coarse indicators. In an effort to maximize the variance of our variables, we use PCA to compute alternative measures. We rely on the first principal component of the three truancy measures (though results are consistent if the first two components are chosen instead).

Results in Table 17 show that the first-stage relationships between each component and slave trade exposure are consistent with our original results. Table 18 follows with the 2-SLS analysis. The negative and significant effect of teacher truancy persists for precisely the same percentiles as our original results – the 83rd and 77th percentiles and above in math and reading respectively.

2.3.1 1-SLS results

Table 17: Alternative teacher truancy measure and slave trade exposure: 1-SLS results

	Dep. var.: PC truancy	
	Math	Reading
	(1)	(2)
Slave trade exposure	-0.001***	-0.001***
	(0.000)	(0.000)
Student characteristics	yes	yes
Classroom characteristics	yes	yes
Teacher characteristics	yes	yes
Other school characteristics	yes	yes
Regional fixed effects	yes	yes
F-statistic	34.0471***	44.141***
DWH χ^2	50.37***	23.94***
R^2	0.418	0.421
Observations	25,351	26,541

Notes: This table reports 1-SLS estimates for average teacher truancy. The unit of observation is the student. We control in both columns for student, classroom, teacher, other school, and regional characteristics, as well as for country fixed effects. Robust standard errors are in parentheses. *, ** and *** indicate significance at the 10, 5 and 1% levels.

2.3.2 2-SLS results

Table 18: Alternative teacher truancy measure and test scores according to student SES: 2-SLS results

	Dep. var.: Test scores	
	Math	Reading
	(1)	(2)
PC truancy	42.762	15.529
	(30.512)	(28.790)
PC truancy*Home possession	-104.189**	-67.834
	(48.347)	(51.087)
$\alpha_{M_s} + 0(\beta_{M_s^* SES}) = 0$	0.16	0.59
$\alpha_{M_s} + 0.07(\beta_{M_s^* SES}) = 0$	0.19	0.67
$\alpha_{M_s} + 0.14(\beta_{M_s^* SES}) = 0$	0.24	0.79
$\alpha_{M_s} + 0.21(\beta_{M_s^* SES}) = 0$	0.32	0.96
$\alpha_{M_s} + 0.29(\beta_{M_s^* SES}) = 0$	0.46	0.80
$\alpha_{M_s} + 0.36(\beta_{M_s^* SES}) = 0$	0.70	0.48
$\alpha_{M_s} + 0.43(\beta_{M_s^* SES}) = 0$	0.87	0.16
$\alpha_{M_s} + 0.50(\beta_{M_s^* SES}) = 0$	0.32	0.02
$\alpha_{M_s} + 0.57(\beta_{M_s^* SES}) = 0$	0.03	0.003
$\alpha_{M_s} + 0.64(\beta_{M_s^* SES}) = 0$	0.002	0.002
$\alpha_{M_s} + 0.71(\beta_{M_s^* SES}) = 0$	0.001	0.004
$\alpha_{M_s} + 0.79(\beta_{M_s^* SES}) = 0$	0.001	0.01
$\alpha_{M_s} + 0.86(\beta_{M_s^* SES}) = 0$	0.001	0.02
$\alpha_{M_s} + 0.93(\beta_{M_s^* SES}) = 0$	0.002	0.02
$\alpha_{M_s} + 1(\beta_{M_s^* SES}) = 0$	0.003	0.03
Student characteristics	yes	yes
Classroom characteristics	yes	yes
Teacher characteristics	yes	yes
Other school characteristics	yes	yes
Regional fixed effects	yes	yes
R^2	0.469	0.527
Observations	25,351	26,541

Notes: This table reports 2-SLS estimates for PC teacher truancy. The unit of observation is the student. We control in both columns for student, classroom, teacher and other school characteristics, as well as for country fixed effects. The lower panel reports the Wald test p-value for $\alpha_{M_s} + x\beta_{M_s^* SES}$, where α_{M_s} is the coefficient of M_s, x is the home possession level corresponding to a given percentile, and $\beta_{M_s^* SES}$ is the coefficient of $M_s^* SES$. Robust standard errors are in parentheses. *, ** and *** indicate significance at the 10, 5 and 1% levels.

References

[1] Conley, Timothy G., Christian B. Hansen, and Peter E. Rossi. 2012. "Plausibly Exogenous." *The Review of Economics and Statistics*, 94(1): 260-272.