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CONSEQUENCES OF SCHOOL RESOURCES FOR EDUCATIONAL ACHIEVEMENT: EVIDENCE FROM BURKINA FASO

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ABSTRACT

This paper examines the determinants of educational achievement in a developing country context, Burkina Faso. We deviate from the extant literature by constructing an aggregate index of school quality from the observable school resources. Also, we account for school choice constraints, faced by children especially in rural areas, as it relates to the geographical inequalities in the distribution of quality schools. These treatments provide an unbiased estimates of the relevance of school resources for academic performance. The empirical approach is based on a two-stage procedure that accounts for supply constraints in school choice. My findings indicate that failure to correct for school choice constraints significantly understates the relevance of school resources for educational achievement, especially in mathematics.

I. INTRODUCTION

Basic education, mostly provided by the government through free primary schooling, has recorded tremendous success on the extensive margin over the past century with about 91% of school-age children gaining access.[1] However, on the intensive margin, less success has been recorded. It has been estimated that about 38% of children, most of whom have spent 4 years in school, are not learning the basics in reading and mathematics (UNESCO Institute of Statistics (UIS), 2015). The quality of education received once children are enrolled, especially in developing countries, is poor because these countries have focused on implementing a linear or sequential model of educational delivery (providing access now and improving quality later) instead of a concurrent model (UNESCO, 2004). The adoption of this model is necessitated by the challenge to meet the development goal of providing universal access to primary education. However, for individuals and economies to enjoy the multifaceted returns to education, getting children into school is not enough. What matters more is that schooling leads to meaningful learning (Pritchett, 2013). Concerned about this observation, governments have invested in supply side interventions that provide more teaching and learning materials, technology, facilities, and nutrition and hygiene (UNESCO, 2016).

This study investigates how the provision of these resources affects educational outcomes of children. An aggregate school quality index that captures the availability of individual school resources is used to measure their relevance for children's academic performance. This is done using a unique dataset from Burkina Faso containing observations primarily on 21,000 individual children aged five to twelve years as well as their household, school and village level data. Furthermore, I exploit the dataset to separate and compare the relative importance of school resources (supply side) and household characteristics (demand side) as they affect academic performance using an identification strategy similar to León and Valdivia (2015). Variation in the distribution of quality schools across villages is used to address the non-random selection of kids into schools of different quality. A host of child, household and village controls are used to minimize omitted variable bias in the analysis.

A number of findings follow from the analysis. First, school resources are important for educational attainment; being in a high quality school increases mathematics and language test scores of primary school children in Burkina Faso by .25 and .12 standard deviations respectively. Second, ignoring the selection bias in school choice significantly understates the relevance of school resources for educational achievement. Third, gaps in educational achievement between high and lower quality schools persist for children with similar socioeconomic background. These findings suggest that in a developing country setting, supply side constraints matter for academic performance of children, even more than their socioeconomic background. Hence, policy should thrust towards equitable provision of school resources if the goal is to improve learning outcomes. Lastly, the analysis suggests that school resource provision in Burkina Faso can encourage more girls to enrol in school.

[1] UNICEF (2013)

This paper has contributed to the literature in three notable areas. First, it provides a new unit of analysis (aggregated instead of individual inputs) for gauging the impact of supply side interventions on test scores. Aggregation captures the interaction of individual resources in the schooling environment. Also, it accounts for the problem of substitutability and complementarity among individual school resources. Second, the study provides additional empirical evidence on the importance of school resources for academic achievement. This understanding is crucial for policymakers in channelling resources to sustain supply side interventions. Third, the study uses a unique dataset that allows for geographical inequalities in provision of quality schools in sampled areas to be exploited in addressing the selection problem in school choice as well as for demand side factors to be accounted. Past studies (see Glewwe et al., 2009; Kremer et al., 2013; Duflo et al., 2015) have overlooked the crucial effect on school resources identification of the non-random selection of kids into schools of different quality, usually influenced by demand side factors such as the socioeconomic background of their families.

The rest of the paper is organized as follows. Section II provides a brief literature review. The reader is briefed on the state of primary school education in Burkina Faso as well as details about the dataset used for the analysis in Section III. The core of the paper is captured in sections IV and V. Section IV describes the identification strategy and empirical model, while Section V contains a discussion of my findings. A brief summary of the paper is provided in Section VI along with concluding remarks and policy suggestions.

II. LITERATURE REVIEW

The vast empirical literature on the effects of school resources on educational achievement has so far yielded mixed results. One of the earliest inquiries into the effects of school resources and family socioeconomic background on students' school outcome was the Coleman Report (1966). Findings in the report showed that the effect of school resources on educational achievement were small and uncertain and family characteristics were more relevant determinants of educational achievement. The Coleman Report (1966) no doubt motivated the subsequent studies on the subject, which have tried to the document experiences in other countries and using alternative methodology to establish causality.

Glewwe et al. (2011) review several studies between 1990 and 2010 and find that school resources have a positive and significant impact on educational achievement in some contexts. Banerjee et al. (2007) find through a randomized experiment in urban India that technology-assisted learning program increased test scores, with gains remaining significant a year after the program ended for targeted children. Muralidharan and Sundararaman (2011) ran a randomized control trial in India and found positive and significant effects of school inputs on academic test scores.

On the other hand, Kremer et al. (2013) review a number of recent randomized control trials and conclude that test scores are unresponsive to providing more traditional school resources, such as buying more textbooks or hiring additional teachers. Various studies reviewed by Hanushek and Woessmann (2011, p. 126) show that family background has stronger effects on school outcomes of children than school resources, with some studies finding no impact of school resources at all on educational outcomes. Glewwe et al. (2009) found that provision of textbooks not only failed to improve test scores on average, but also exacerbated within-class inequalities by aiding only stronger students that can read them. Duflo et al. (2015) report that a drastic decrease in average pupil-teacher ratio failed to improve test scores. Provision of teaching aids was found not to have any significant effect on test scores by Glewwe et al. (2004) in a randomized experiment. Despite the positive health and attendance improvements witnessed with the administration of deworming medicine in Kenya, there was no evidence of test scores being affected (Kremer & Miguel, 2004).

Three critical points arise from reviewing the existing literature. First, the studies focus on a single school resource in trying to identify the effects of school resources on educational achievement. Although these individual inputs are normally correlated with school quality, singling them out and trying to identify their effect can lead to misleading results as other inputs respond to changes in the resource of interest due to substitutability and complementarity. Das et al. (2013) show why it is important to take account of optimizing household responses to changes in school inputs, which tends to crowd out the effects of school inputs on test scores. Responses such as the optimal reallocation of household resources in response to anticipated changes in school inputs indicate that careful thought needs to be given to how school inputs work in enhancing educational attainment. Since all elements of a schooling environment influence how well a child performs academically, this paper does not focus on a single school resource. Rather, I use a scalar school quality index that captures all the school inputs of interest. This way, I hope to capture major areas of strength and weakness in a school that are capable of affecting test scores.

Second, a survey of literature makes it evident that the relationship between school resources and educational achievement is nonlinear (Hanushek, 2003). There are diminishing returns to school resources; they seem to be most important where they are scarce and do well in improving educational outcomes but become irrelevant in doing so when there is no quality constraint on the supply side. Third, the endogeneity of school choice is usually not accounted for, which can significantly overstate or understate the importance of school resources for educational achievement based on availability of quality schools.

This study uses data from a developing country (Burkina Faso), where school resources are scarce and potentially most important in improving educational outcomes. However, unlike most studies in the literature, school resources are to be consolidated to form a unilateral school quality index. This is to allow us see how a mixture of the various school inputs (that have been shown to affect learning and educational achievement) affect test scores when aggregated. Further, the endogeneity of school choice on the part of parents is often ignored. This study addresses this by using a two-step procedure similar to one in (León & Valdivia, 2015). My identification strategy relies on the geographical inequalities connected to school resources across villages in Burkina Faso.

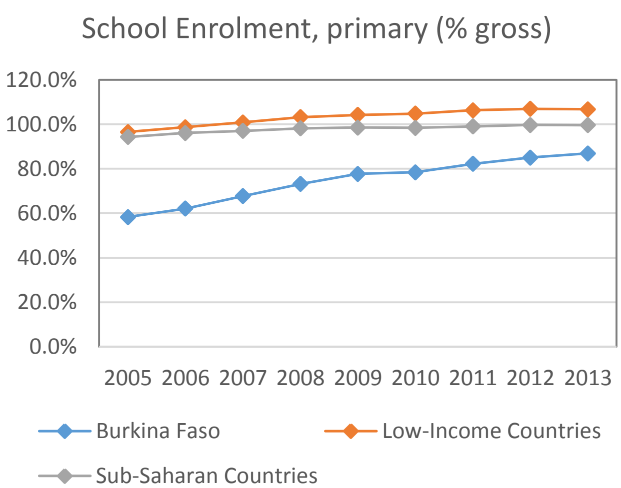
III. BACKGROUND, DATA AND DESCRIPTIVE STATISTICS

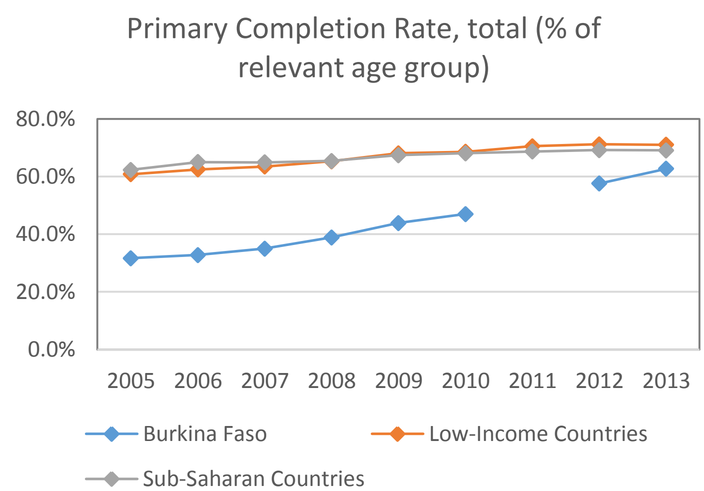
Primary School Education in Burkina Faso

Children of relevant ages attend primary school for free in Burkina Faso. However, it is usual for households to still be required to finance some learning-related expenditure in addition to the opportunity cost of sending their children to school. Primary schooling lasts for six years officially, but there are cases of grade repetition and overaged kids finishing after they have turned 12 years old. A national examination at the end of grade six determines progression to secondary school. By law, schooling is compulsory till age 16. The practice does not mirror this due to infrastructural deficiencies, especially in rural areas. Therefore the law is not enforced (Levy, et al., 2009).

Educational attainment is a primary concern in Burkina Faso. It performs poorly on educational development indicators, even when compared with other low income countries. The expected years of schooling is 6.9 years in Burkina Faso, much lower than Sub-Saharan and low-income countries average of 9.3 and 8.5 years respectively (UNDP, 2013). Despite the improvements recorded over the years, Burkina Faso remains behind other Sub-Saharan and low-income countries on education indicators (Figure 1).

Figure 1: Comparing Burkina Faso's Educational Attainment to other Countries





Source: The World Bank (2013)

Much of the improvement seen in the trend is a result of the government partnering development partners in trying to achieve the Millennium Development Goals (MDGs). It is however important for the progress to be sustained and improved upon given that 25% of Burkina Faso's population are under age five and the country's population of over 17 million is expected to double in a generation (The World Bank, 2015). The looming population crises puts development and poverty alleviation efforts in jeopardy. Thus these challenges of development mean that the government of Burkina Faso cannot afford to implement a linear or sequential model of educational delivery. Rather, it must concentrate on implementing a strategy that yields results. Improving quality must be integral to any development program aimed at increasing educational access, retention and achievement. This is why this paper is especially important for advising education policy in Burkina Faso going forward.

Data and Descriptive Statistics

This paper uses a dataset collected by Mathematica Policy Research, Inc. in 2007 from 132 villages in Burkina Faso across 287 villages (Millennium Challenge Corporation, 2014). It contains observations primarily on a random sample of over 21,000 individual children between the ages of five and twelve. Also contains household level data, school level data, and village level data that have been merged into one dataset. The dataset contains math and language test scores of children, their household characteristics along with the characteristics of the schools which they attend. 270 schools were sampled across selected villages and information collected were matched with more than 7,400 children in the sample.[2]

About 60% of children in the dataset do not attend school. Households in the datasets differ on the reasons why they choose not to send their children of relevant age to school. 28.46% of households that do not send their children to school report doing so because they believe the child is too young. Other reasons outlined by households with children not enrolled in school include unavailability of schools in the village (21.82%), household work (20.76%), school fees (13.15%), and distance to school being too long (5.04%). The enrolment rates in the dataset differ from the national average because the data was collected from targeted villages with the lowest enrolment rates that were to take part in a program to improve educational attainment.

The test scores recorded in the dataset were gotten from mathematics and French language tests that data collectors administered to the sampled children. This suppresses the usual test scores concern in education research about cheating and test paper leaks and provides external validity of the children's performance. However, a drawback of the testing method used is that all sampled children, of ages five to twelve, were administered the same test irrespective of their enrolment status or grade in school. Therefore, as expected kids in higher grades performed excellently on the test while those not enrolled in school or just started school did not do so well. Noting this characteristic of the dataset allowed me to control for any possible bias it may cause in the analysis. I constructed grade dummies to indicate which class children in the sample are and controlled for this observation.

Lastly, in order to have a measure of socioeconomic conditions in each village, I use a scoring system made available in the dataset. It was used to assign villages to the control or treatment group based on the rank of the village by need or poverty. It is normalized around zero and villages with positive scores made the treatment group while those with negative scores were the control group. The definitions of variables used in the empirical analysis are detailed in T*able 1*.[3]

[2] The number of observations effectively used in the empirical analysis is slightly below 7,400 because of some observations having missing values in variables of interest.
[3] Table A.1 contains the descriptive statistics of these variables.

Table 1: Description of Variables Used in the Empirical Analysis.

Variable	Description
Mathematics and language	
Standardized score	Standardized test score in Math and Language. The original scores are normalized.
Child's gender	Pupil's gender, = 1 if boy.
Attendance past week	Number of days the pupil went to school in the past week.
Highest level of schooling in the household	Highest level of schooling among parents or guardians. 1 = No education, 2 = Incomplete Primary, 3 = Complete Primary, 4 = Incomplete Secondary, 5 = Complete Secondary, 6 = More than Secondary education.
Household asset index	An Asset Index computed using principal component analysis with households' dwelling characteristics and asset ownership. See Section 3 for an explanation of its construction and Table A.2 for the descriptive statistics of the considered variables.
Grade dummies	6 dummy variables indicating the class a child attends.
Pupil-teacher ratio	The number of pupils per teacher in the school.
Textbook availability	Categorical variables indicating whether the school provides pupils with textbooks. 0 = No, 1 = Yes, for use in school and 2 = Yes, can take home.
Teacher absenteeism	Percentage of time a typical teacher in the school is absent
Feeding program	A dummy variable indicating whether the school runs a feeding program.
Village poverty score	A normalized poverty score of the village.

Source: (Millennium Challenge Corporation, 2014)

IV. METHODOLOGICAL APPROACH

The quality of schools can vary significantly due to several factors. School quality in general is difficult to quantify and ranking schools according to resource availability is challenging. However, there are some resources that can be considered, which can potentially give a simple categorization of schools. Their relative importance in determining the quality of a school is also of importance. Therefore, I use principal component analysis to construct a scalar school quality index with the considered variables, which enables me see the input of the relevant resources into my quality measure.

The Burkina Faso dataset provides detailed information on the schools the sampled children attend. I use this data to create an index that will enable me to rank the schools in the sample. The ranking further aids in classifying the schools into three categories; low, medium and high quality schools. Observable school characteristics that have been shown in previous studies to affect educational achievement are the basis of the said index. The observable school characteristics considered are:

(i) Class size, measured by the pupil-teacher ratio. Numerous studies (Angrist and Lavy, 1999; Case and Deaton, 1999; Hanushek, 2003) have shown class size to be one of the most important school characteristic that influences educational attainment. For instance, Angrist and Lavy (1999) show that reducing class size leads to a substantial and significant increase in pupils' test scores.

(ii) Learning resource availability, which I proxy by the provision of textbooks by a school. Quite a number of studies (Glewwe, et al., 2011; McEwan, 2015; Tan, et al., 1999) have shown that learning resources are essential in influencing learning outcomes. In his meta-analysis of over 77 randomized experiments, McEwan (2015) found instructional materials to be in the class of school inputs with the largest mean effect.

(iii) School organization, measured here by teachers' attitude towards instruction or pedagogy, proxied by the level of absenteeism in a school. Almost all the high quality studies on teacher absenteeism from 1990 to 2010 reviewed by Glewwe et al. (2011) reported negative and significant effects on test scores. High quality school should be better organized and exhibit professional teacher conduct.

(iv) School feeding program, measured by whether a school provides meals for pupils or not. It is common for schools in my dataset to have feeding interventions running in schools. 83.8% of schools in the sample have a feeding program. This is the school resource that research suggests to have the most inconclusive evidence of impacting learning outcome (Vermeersch & Kremer, 2005). I include it in the index because school meals have the potential to improve educational outcome by affecting child nutrition and also discourage kids from being absent. Further, the interplay of all considered school resources provide new insight into how school quality affects learning outcomes together.

The first principal component from the four variables described above was retained as a summary measure of overall school quality. The first principal component explains 34% of the total variance of considered variables. *Table 2* shows the coefficients associated with each of the four variables considered in the principal component analysis. While *Figure 2* shows the kernel density of the predicted first principal component. It is obvious from the figure that there is no glaring or natural classification of school into groups. Rather than having modal groups of schools based on their scores for component one, schools in the sample tend to be clustered together.[4] Nonetheless, I use terciles of the first component to classify schools into three categories – low quality (93 schools), medium quality (91 schools), and high quality (93 schools)

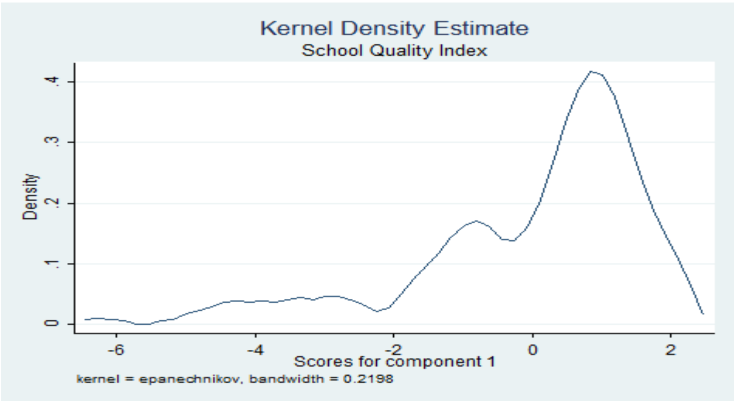
[4] This is also true for the only continuous individual resource (pupil-teacher ratio) used in the PCA (see Fig A.1). Hence, I attach more importance on the first component from the PCA as my scalar school quality index in the analysis ignoring the endogeneity of school choice. I also run the analysis with the alternative classification of schools into three groups, which is important for my two-stage identification strategy.

– as this is important for my identification strategy controlling for the endogeneity of school choice.

Table 2: Principal Component Analysis - School Quality Index

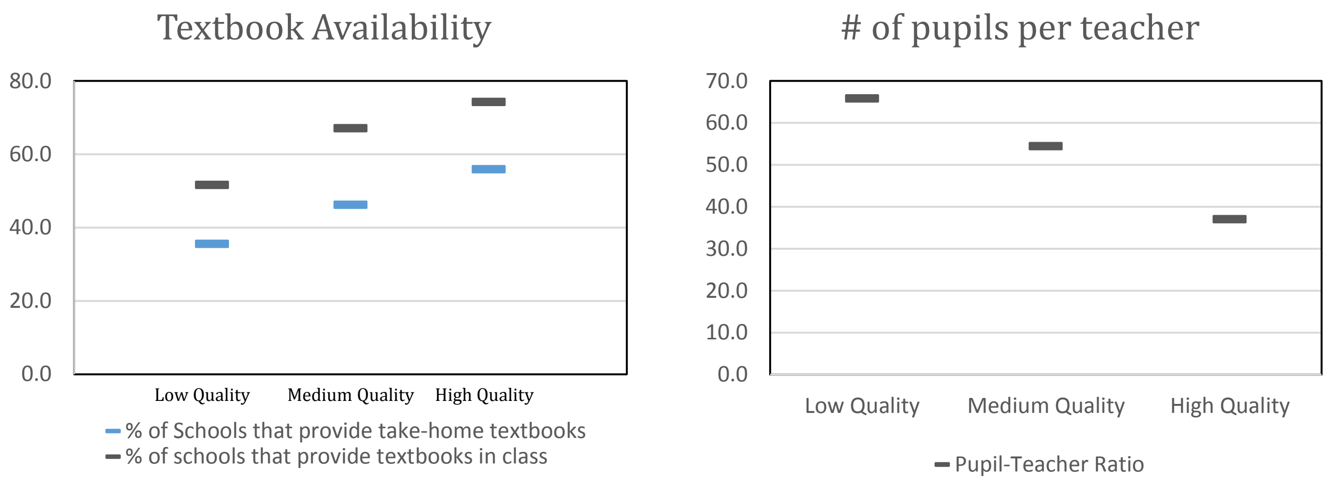
	Coefficient	Mean	Std. Dev	Min	Max
Pupil-teacher ratio	−0.3753	52.4	21.235	15	130
Textbook availability	0.1160	1.1	0.898	0	2
Teacher absenteeism (%)	−0.0600	5.8	4.363	2	20
Feeding program	0.3512	0.8	0.369	0	1
Percentage of overall variability explained by the first principal component[5]	34.07%				

Figure 2: Empirical Distribution of the School Quality Index.

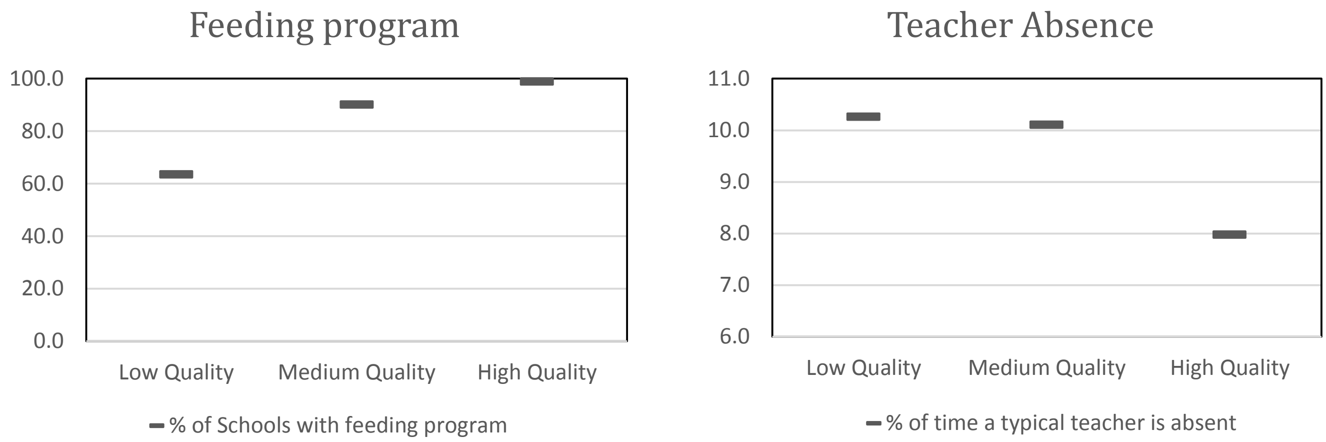


Note: The figure illustrates the kernel density estimate for the school quality index constructed by all the school in the sample. (See Fig A.2 for alternative representation)

Figure 3. Mean of Variables Considered for School Type.



[5] This is calculated by taking the ratio of the eigenvalue of the first component to the sum of the eigenvalues corresponding to all eigenvectors in the PCA – $\frac{\lambda_1}{\sum_{i=1}^{4}\lambda_i}$.



Notes: The figure shows the averages of each of the variables considered in the school quality index, for each type of school. The sample includes all schools in the sample. 93 schools are classified as low quality, 91 medium quality, and 93 are high quality.

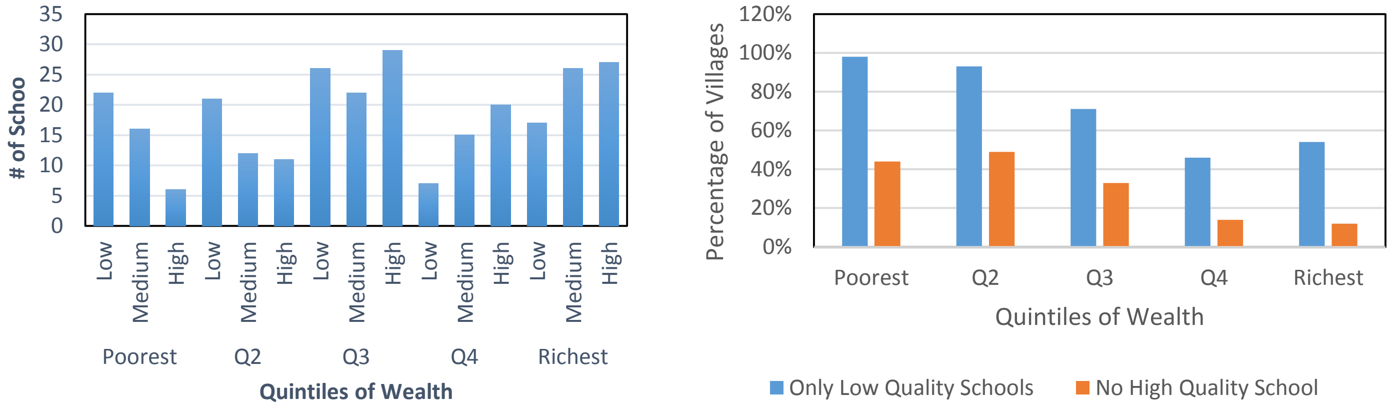
This classification presents noticeable differences between school categories. *Figure 3* shows the mean of the variables considered in the school quality index, for each school type defined. Categories of schools scored as expected on average in all of the areas. High quality schools performed best on all considered indicators: they have the smallest class sizes with an average pupil-teacher ratio of 37; 74.2% of schools provide textbooks for use in class for their pupils and 55.9% of schools provide textbooks for their pupils that they can take home; teachers are absent 8% of the time on average; and 98.9% of schools run a feeding program.

The geographical distribution of quality school is not homogenous. Poor villages face more severe quality constraint, while wealthier villages enjoy a more relaxed supply of schools. Panel A of *Figure 4* shows the number of schools of each type per quintiles of village wealth (based on the normalized poverty score of the village); while Panel B contains the plot of the percentage of villages with choice constraints per quintile of wealth. The first bar shows the percentage of villages with only schools of low quality, while the second bar shows the percentage of villages with no high quality schools. We see an association between wealth level of a village and the choice set of schools available to households. This geographical inequality of school resources might have an impact on the academic achievement of children in poorer areas, who are forced to receive lower quality education because there are no high quality schools.

One concern with this line of argument is that though children in poorer villages face quality constraints, their parents can overcome this by moving to areas with better schools. However, migration for the sake of primary school attendance is not common in Sub-Saharan Africa. Migration occurs mainly due to economic reasons, where people move to cities to look for employment. Migration for the sake of attending boarding secondary school is not uncommon though. Teens, especially from poor villages with no secondary schools of suitable quality, are often sent to bigger towns to attend secondary school. However, families do not migrate to enable their kids attend better primary school. Potential bias from migration decisions would not constitute a problem here since my sample consists of only children of primary school age.

Figure 4: Number of Villages with Choice Constraints by Quintiles of Wealth.

A



Panel A: availability of school of each type, by village wealth. Panel B: supply side constraints of each school type, by village wealth. Notes: Panel A shows the number of each type of school available in villages, by quintiles of wealth. Panel B shows the number of villages in which there are only some types of schools.

Separating the role of household and parent characteristics vis-à-vis school resources

The relative importance of school and household characteristics has drawn significant attention in the literature. Large school effects are often suggested when academic performance of children from schools of different quality is compared. However, simply accounting for socioeconomic background makes most of the positive effects of high quality school decline. In the following, I describe the methodological approach that will allow me separate the role of school inputs vis-à-vis parent and household characteristics.

I first compute a measure of socioeconomic status using observable household characteristics. *Figure 5* shows the mean difference in educational attainment of children by the type of school they go to and socioeconomic status, measured by an asset index (AI).[6] We can see a mild upward trend in educational attainment, measured by mathematics and language scores, as we move to richer quintiles of AI. Gaps in educational attainment between high and lower quality schools usually reduce once socioeconomic status is controlled for. This is not the case in the Burkina Faso data. Gaps in educational attainment remain wide even for kids in the same quintile of AI, especially for mathematics. It is less pronounced in the case of language scores. School quality appear to dominate socioeconomic condition in determining learning outcomes. Nonetheless, I am careful not to conclude anything from a univariate correlation. All other relevant characteristics have to be controlled for.

[6] I use principal component analysis to construct this index with a set of asset ownership variables described in Table A.2.

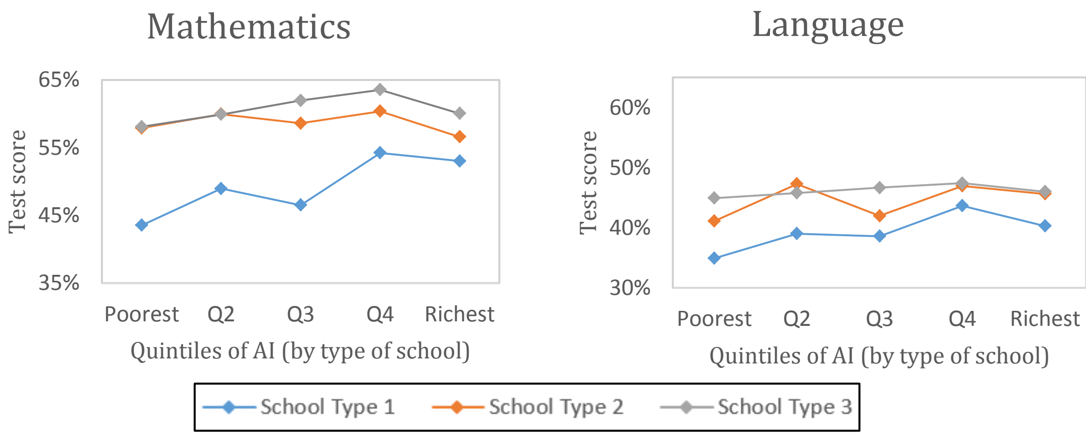


Figure 5: Difference in Educational Attainment, by School Type and Socioeconomic Status

I evaluated a multivariate model to separate the relative importance of child, parent, household, school, and village characteristics on educational outcome of primary school pupils in Burkina Faso. Test scores in Mathematics and Language are used as a proxy for educational attainment. There are two important challenges to estimating this model. Firstly, there could be unobserved village or school characteristics correlated with both socioeconomic status and school resources. Secondly, there is the selection problem whereby poor pupils are the ones sorting into schools of low quality.

My first specification accounts for the omitted variable bias, leaving the selection problem. If we understand school environment to be important, an ordinary least squares (OLS) model would be affected by unobservable household, school, and village characteristics generating consistent but inefficient estimates.[7] Since it is likely that unobserved heterogeneity of children does not affect the covariates (school quality, household's socioeconomic status or village wealth). If the unobserved school characteristics are orthogonal to the observed school and household variables, then a random effects model at the school level will yield efficient (minimum variance) estimates. The formal representation of the model to be estimated is:

$$y_{ijk} = \beta_o + Q_{jk}\gamma + H_{ijk}\beta_1 + V_k\beta_2 + \alpha_{jk} + \varepsilon_{ijk} \qquad (1)$$

$$y_{ijk} = \beta_o + \sum_{n=1}^{3} Q_{jk}^{n}\gamma_n \ + \ H_{ijk}\beta_1 + V_k\beta_2 + \alpha_{jk} + \varepsilon_{ijk} \qquad (2)$$

where y_{ijk} denotes the Mathematics or Language test score of student *i*, attending school *j* in village *k*. In equation (1) Q_{jk}represents the (continuous) scalar quality index of school *j*, while in equation (2) Q_{jk}^{n} are three indicator variables indicating whether pupil *i* attends a type 1, 2, or 3 school, representing school *j*'s observable quality. H_{ijk} is a vector of individual and household characteristics. V_k denotes a vector of observable village characteristics, α_{jk} denotes school *j*'s

[7] See **Invalid source specified.**, Chapter 13.4

unobservable characteristics, which are assumed to be uncorrelated with observed school and household characteristics. ε_{ijk} is the random error term.[8]

The use of alternative specifications with different measures of school quality is to address the concern pointed out above of not having a natural classification of schools as seen on the kernel density function of the quality index. Where the use of terciles to force the schools into the categories fails to represent the quality of schools, the scalar school quality index will do so.

In specifications (1) and (2), my interest lies in the magnitude and significance of γ and γ_n, respectively. These correspond to the sign and significance of school resources in explaining educational achievement. Nonetheless, the pitfall of these econometric specifications is that they fail to account for the fact that parents decide on schools their children attend.

Addressing the Selection Problem

Many of the empirical studies that seek to find the relationship between school resources and educational outcomes fail to account for the endogeneity of school choice. The school a child attends is not exogenous, it is guided by parents' preferences, which are affected by their socioeconomic condition. The tendency of rich and educated parents to send their kids to schools of higher quality cannot be dismissed in analysing how changing a school input affects children's performance. However, this choice is ultimately dependant on the availability of appropriate options. Due to supply constraints faced by households especially in rural areas, some are unable to send their kids to a school of desired quality.

Failure to control for availability of suitable schools might lead to bias in estimated coefficients of school resources and household characteristics in an education production function. The sign of the bias depends on geographical inequalities in the distribution of quality schools. If a village has schools of different quality, households that are richer, more educated and value investing in education will tend to send their children to high quality schools while the opposite might happen for households with relatively lower economic and human resources. This selection makes children in different schools essentially different and might overestimate the effect of school resources. On the other hand, if the supply of quality schools is constrained in a province, children from different backgrounds end up in the same school and the bias in the effect of school resources might be downward; if only low quality schools are available.

In trying to identify the effects of school resources on educational attainment, the ideal experiment will be to have children randomly assigned to schools with and without the resource of interest irrespective of their socioeconomic background. Randomly assigning children of various socioeconomic backgrounds into schools of different quality and comparing their educational outcomes ensures that the causal effect of school quality or providing a school input of interest is captured. However, this scenario is not attainable in the real world and such an experiment is not available. The next best thing is to compare the educational achievement of

[8] The required assumptions on the error term ε_{ijk}, and the random term δ_{jk} are: $E[\varepsilon_{ij}|H,Q] = E[\delta_j|H,Q] = 0, E[\varepsilon_{ij}^2 ZH,Q] = \sigma_\varepsilon^2; E[\delta_j^2|H,Q] = \sigma_\delta^2, \forall\, i,j,k: E[\varepsilon_{ij}\delta_k|H,Q] = 0, \forall\, i \neq k, j \neq l : E[\varepsilon_{ij}\varepsilon_{kl}|H,Q] = 0\,;\ \forall\, i \neq j : E[\delta_i\delta_j|H,Q] = 0$.

children that are forced to attend schools of different quality for reasons unconnected to their socioeconomic background. I compared children with similar household and socioeconomic background; while some are able to go to a school with suitable quality as chosen by their parents, others were restricted to going to the school type available in their village. My identification strategy specifically exploits the geographical inequalities in the choice set of parents to estimate the effect of school resources on educational achievement, following a two-step procedure similar to one in (León & Valdivia, 2015). More precisely, I use the availability of classes of each school type in village *k* to instrument for the type of school a child goes to.

The two-step procedure estimates a local average treatment effect, which represents the causal effect of school quality on educational achievement for the children whose choices are hindered by the availability of suitable schools. The causal effect estimates are only valid for children who would have gone to a school of different quality had it been available. No additional traction will be gotten from children who would have still attended a school of the same time irrespective of a supply constraint. For instance, if a child lives in a village with only low quality schools but would have gone to a low quality school even if other options were available, there will be no additional traction from such a child. However, if there are other children in that same village that would have gone to a medium or high quality school had they been available, the estimator will pick exactly this variation.

For a valid instrument, the exclusion restriction requires that the number of classrooms of the respective school types in a village only affect educational achievement through the school type to which a child attends. A concern one may harbour is that the availability of schools of a certain type is correlated with the wealth level in the village. I use the normalized poverty score of a village to control for the general wealth level in the village. Once this is controlled for, the conditional correlation between the instrument and the error term in the second stage as a result of village characteristics should wane. It is easy to see why the number of classrooms of each type of school in a village is a relevant instrument for school availability.

The idea here is to instrument the effect of every type of school using information about the types of schools available in the villages where children in the dataset live, accounting for the different selection process when the village offers only low quality schools than when it has schools of better quality. In the first instance, given the constraints, there is no much room for a decision, while in the latter instance, perhaps some unobservable factors explain the reason for parents' decision to send the child to a low quality school, despite the available option of better quality schools in the same village.

As earlier noted, I formed three categories of schools, depending on observable school resources. I then computed the number of classrooms of all types of schools in each village. This information becomes useful in the two-step identification strategy to compute, first, the effects of school availability on the school type a child goes to, and then the effect of this school type on educational outcome. In stage one, I estimate a multinomial logit model to determine the decision process in selecting the type of school where every child in my sample attends.

Stage One: Multinomial logit model[9]

$$Q^*_{ijk,l} = H_{ijk}\theta_1 + NC1_k\theta_2 + NC2_k\theta_3 + NC3_k\theta_4 + \delta_j + \epsilon_{ijk} \tag{3}$$

where Q^*_{ijk} is the school type of the j^{th} school, where student i in village k attends. $NC1_k, NC2_k, and\ NC3_k$ represent the number of classrooms in schools of type 1, 2 and 3 operating in village k. Using the number of classrooms available in each type of school enables me identify the system and works fine as a good instrument, since it is likely that the number of classrooms of each type of school is related to the choice of school parents make, but it is plausible to assume that it is orthogonal to children's performance on tests, their unobserved ability, or household characteristics (conditional on certain variable). Note however that the estimation is not done on Q^*, but on Q, hence:

$$P(Q_{ijk} = 1) = P\left(\max\left(Q^*_{ijk,1}, Q^*_{ijk,2}, Q^*_{ijk,3}\right) = Q^*_{ijk,1}\right)$$
$$P(Q_{ijk} = 2) = P\left(\max\left(Q^*_{ijk,1}, Q^*_{ijk,2}, Q^*_{ijk,3}\right) = Q^*_{ijk,2}\right)$$
$$P(Q_{ijk} = 3) = P\left(\max\left(Q^*_{ijk,1}, Q^*_{ijk,2}, Q^*_{ijk,3}\right) = Q^*_{ijk,3}\right)$$

In the first stage, I back out the probability that the school child i attends is of type 1, 2 or 3 assuming ϵ_{ijk} follows a logistic distribution.

$$\hat{Q}_{ijk,1} = \Pr(Q_{ijk} = 1|\boldsymbol{X}) = \frac{1}{1 + \sum_{l=2}^{3} \exp(\boldsymbol{\gamma}_l \boldsymbol{X}_{ijk})}$$
$$\hat{Q}_{ijk,2} = \Pr(Q_{ijk} = 2|\boldsymbol{X}) = \frac{\exp(\boldsymbol{\gamma}_2 \boldsymbol{X}_{ijk})}{1 + \sum_{l=2}^{3} \exp(\boldsymbol{\gamma}_l \boldsymbol{X}_{ijk})}$$
$$\hat{Q}_{ijk,3} = \Pr(Q_{iijk} = 2|\boldsymbol{X}) = \frac{\exp(\boldsymbol{\gamma}_3 \boldsymbol{X}_{ijk})}{1 + \sum_{l=2}^{3} \exp(\boldsymbol{\gamma}_l \boldsymbol{X}_{ijk})}$$

where $\boldsymbol{X}_{ijk}$ denotes the vector of covariates.

Following instrumenting in the first stage, I estimate the effect of school types on educational performance using a random effects model in the second stage:

Stage Two: random effects model

$$y_{ijk} = H_{ijk}\beta_1 + \sum_{n=1}^{3} \hat{Q}^n_{jk}\gamma_n + V_k\beta_2 + \delta_{jk} + \eta_{ijk} \tag{4}$$

A comparison of estimates from equations (2) and (4) enables me estimate the relevance of supply side constraints on the educational achievement of Burkinabe children. Notice that observable village characteristics associated with socioeconomic status are controlled for. I however cannot disregard possible bias that might arise from the omission of unobserved village characteristics that are correlated with the availability of school types.

[9] For robustness, ordered probit and ordered logit models were used for the choice model and find similar results. These are not reported though.

V. SCHOOL RESOURCES AND EDUCATIONAL ACHIEVEMENT: ECONOMETRIC ANALYSIS

In this section, I show and discuss the results of the estimation of school impact. I consider the first equations (1) and (2) [10] that deal with the omitted variable problem first and then focus on the school effects after the application of the two-stage procedure described in equations (3) – (4).

The school effect: omitted variables

Table 3 reports the coefficients of interest for children who took the math and language tests using equation (1). Household characteristics, such as the socioeconomic status and the level of schooling of the most educated member of the household appear not to matter at all for the child's educational performance in this regression.[11] The same goes for village characteristics, with the normalized poverty score taking on a negative sign though only statistically significant in the language test. Observable individual characteristics seem to do well in influencing test scores. The gender of a child significantly affects their learning outcome in the language specification though with little magnitude; being a boy on average increases the normalized language test score by 4.6% of a standard deviation. Other individual characteristics such as the child's age and attendance rate positively and significantly influence test scores. The variable of interest, school quality, increases mathematics and language scores by .09 and .06 standard deviations respectively, significant at the 1% level.

Table 3: Determinants of educational attainment in Burkina Faso. Equation (1)

	Random Effects Model			
	Mathematics		Language	
School quality index	.0938	.1439	.0557	.1169
	(.0097)***	(.0229)***	(.0112)***	(.0236)***
Child's gender (1 = boy)	.0295	.1059	.0462	.1355
	(.0187)	(.0250)***	(.0215)**	(.0281)***
Highest level of schooling in the HH	−.0037	−.0196	.0182	−.0072
	(.0086)	(.0212)	(.0098)*	(.0244)
HH asset index	.0112	.0323	.0205	.0451
	(.0100)	(.0205)	(.0115)*	(.0216)**
Village normalized poverty score	−.0105	−.0005	−.0239	−.0171
	(.0092)	(.0297)	(.0106)**	(.0360)
Constant	1.0605	.8219	.3007	.7703

[10] Equation (2) results are reported later alongside those of equation (4) for comparison.

[11] Assets considered in generating the asset index include things like cattle ownership. It is likely for children in households wealthy in livestock to be engaged for longer hours catering for them. Hence, it is within the range of possibility for this measure of rural wealth to harm a child's dedication to school work.

	(.5652)*	(.0356)***	(.6495)	(.0411)***
Grade dummies	Yes	No	Yes	No
Observations	7342	7348	7345	7351
R-sq.	.408	.064	.367	.045

Robust standard errors clustered at the school level in parenthesis.
* Significant at 10%. ** Significant at 5%. *** Significant at 1%.
Note: Specification with grade dummies shown due to testing of all sampled children with the same questions irrespective of enrolment status or grade attended.

Results of the same specification not accounting for the stage a child is in his/her schooling are also reported in *Table 3* Columns 4 and 5. The model did not appear to fit the data. Close examination revealed that this is due to the survey method used in collecting data. Interviewers had a set of basic logic/math and language questions which they administered to the children sampled whether they attended school or not and no matter the level they were in primary school. I remedied this by including grade dummies in the regression and although some coefficients lost value and significance, the model did better in explaining the data.

Ignoring the selection problem and assessing these results will imply that school resources are more important in determining educational attainment than household and parent characteristics. Hence, policy efforts should be geared towards insuring that schools are fully equipped with relevant resources rather than towards the demand side, in as much as the goal is to improve educational attainment. This blends in well with the idea that through proper education, children can break socioeconomic barriers. Although the omitted variable concern was dealt with in estimating these results, too much attention cannot be given to them due to another important problem, the endogeneity of school selection.

The school effect: endogeneity controls

Table 4 reports the coefficients for the choice model in equation (3). Household characteristics, such as the highest level of schooling of the most educated member of the family and the socioeconomic status, do not seem to matter for the choice of school the child attends in Burkina Faso. They all turn out to be statistically insignificant in the choice model, with the exception of the household asset index, which is surprisingly associated with a .315 decrease in the relative log odds of being in a high quality school vs. a low quality school. I include in the regression the normalized poverty score of the village to proxy for the wealth level of each village to make sure that estimators gotten for the supply of classrooms are not capturing other observable characteristics of the locality. The wealth level of a village is not statistically significant in affecting the probability of attending a high quality school. Being a boy makes a child less likely to attend a high quality school than lower quality schools.[12]

[12] One hypothesis that may explain this is that provision of incentives such as running a feeding program in schools makes households more willing to send girls to school. Since feeding program entered the measure of quality used in school classification, the high quality schools must have been more viable options for parents considering sending their girls to school. Resulting in girls being more likely to be in high quality schools vs. low quality schools. Hence,

Table 4: Multinomial Logit Model for the decision of child's school

School type	Coefficient	Robust Std. Err.
Low	(base outcome)	
Medium		
# of classes of type 1 schools in the village	−.8060	(.5623)
# of classes of type 2 schools in the village	.7656	(.4292)*
# of classes of type 3 schools in the village	.4049	(.3846)
Child's gender (1 = boy)	−.1513	(.0813)*
Highest level of schooling in HH	−.1132	(.0833)
HH asset index	−.0685	(.1497)
Village normalized poverty score	.2656	(.2184)
Constant	−.0147	(.6162)
High		
# of classes of type 1 schools in the village	−.5092	(.1504)***
# of classes of type 2 schools in the village	−.2086	(.5156)
# of classes of type 3 schools in the village	2.6382	(.2786)***
Child's gender (1 = boy)	−.3611	(.1218)***
Highest level of schooling in HH	.0248	(.1622)
HH asset index	−.3146	(.1769)*
Village normalized poverty score	.0786	(.2432)
Constant	−1.8787	(.6510)***
Observations		7506
Pseudo R-sq.		.715
Wald Chi^2		278.46
Log pseudolikelihood		−2348.96

* Significant at 10%. ** Significant at 5%. *** Significant at 1%.

Importantly, as seen in *Table 4*, the availability of quality schools in a village, defined by the number of classrooms of each type of school in the village significantly influences the school a child attends. The presence of classrooms of low and medium quality schools in the village reduces the chances of a child to attend a high quality school. However, the presence of classrooms of high quality schools increases the probability of the child attending a high quality school. Increasing the number of high quality schools in a village by one is associated with a 2.64 increase in the relative log odds of attending a high quality school over a low quality one.

school resource provision can aid in improving the low enrolment rates witnessed in Burkina Faso, especially among girls.

This result is statistically significant for the children in my sample. Overall, the distribution of quality schools, across 187 sampled villages, affects the effective access of Burkinabe children to quality education.

Table 5 reports the coefficients from estimating the random effects model in equation (2) with the different types of schools. It also reports the coefficients from estimating the two-stage random effects instrumental variable model in equation (4) alongside for comparison. I put them together so that we can determine the effect of accounting for the school selection decision on the part of parents, in the presence of supply constraints. There are two possible scenarios. If the estimated school effect after controlling for the endogeneity of school choice is lower than that of the random effects model assuming random distribution of school, children from richer and more educated households are the ones sorting into high quality schools, thus have higher educational attainment. In this situation, policy implication will be to focus on demand side interventions because household characteristics would be more important in determining educational attainment. Conversely, if the school effect after controlling for the school selection is higher than the estimate when it is ignored, then the supply constraint of high quality schools would be hindering children's educational attainment, hence policy should be geared towards supply interventions; striving for a more equitable distribution of quality schools or school resources.

Table 5: Determinants of school attainment: comparing equation (2) and (4) estimates.

	Mathematics		Language	
	RE	RE-IV	RE	RE-IV
Attends school type 2	.1538		.1011	
	(.0232)***		(.0267)***	
Attends school type 3	.1940		.0832	
	(.0235)***		(.0270)***	
Predicted probability attends school type 2		.2716		.1701
		(.0857)***		(.1074)
Predicted probability attends school type 3		.2452		.1237
		(.0824)***		(.0961)
Child's gender (1 = boy)	.0280	.0312	.0442	.0426
	(.0188)	(.0189)*	(.0215)**	(.0232)*
Attendance past week	.0272	.0266	.0693	.0699
	(.0097)***	(.0223)	(.0111)***	(.0281)**
Highest level of schooling in the HH	−.0057	−.0048	.0183	.0202
	(.0086)	(.0152)	(.0099)*	(.0180)
HH asset index	.0109	.0115	.0187	.0183
	(.0100)	(.0187)	(.0115)	(.0207)
Village normalized poverty score	−.0101	.0154	−.0242	−.0229

	(.0093)	(.0223)	(.0107)**	(.0263)
Constant	.9583	.9240	.2563	.1155
	(.5660)*	(.7257)***	(.6501)	(.5963)
Grade dummies	Yes	Yes	Yes	Yes
Observations	7342	7348	7345	7351
R-sq.	.408	.406	.370	.369
Wald Chi^2				

Robust standard errors clustered at the school level in parenthesis.
* Significant at 10%. ** Significant at 5%. *** Significant at 1%.

From the results reported in *Table 5*, the estimates are consistent with the second scenario, the hypothesis that solicits supply side interventions. When the random effects model that disregards the selection problem in equation (2) is estimated, the school effects are relatively small compared to that of the instrumental variable model accounting for the endogeneity of school choice, more so for mathematics. Attending a type 3 school (high quality) increases educational attainment by .19 and .08 standard deviations in mathematics and language respectively, both significant at the 1% level. The characteristics of the medium quality schools increase mathematics and language scores by .15 and .10 standard deviations respectively. The comparison group are the low quality schools, which are the omitted category.

Columns 3 and 5 of *Table 5* report the school effects when using the two-stage correction method to account for the bias in geographical distribution of quality schools. After controlling for the limited availability of schools, attending a medium or high quality school has a positive and significant impact on children's performance in mathematics but not for language. These school effects are larger than the one estimated in column 2, when the selection bias was ignored. In mathematics, the effect went from .19 to .25 standard deviations for high quality schools, while for language, the effect seem statistically irrelevant. The effect for medium quality schools in mathematics went from .15 to .27 standard deviations, while becoming statistically insignificant for language.[13] These estimates for medium and high quality schools are close and equally statistically significant in both mathematics and language, though point estimates are ordered the wrong way.

Household characteristics and village characteristics replicate what we see in *Table 3*. They appear not to matter for educational achievement. As for individual characteristics, boys are more likely to perform slightly better in both mathematics and language in my instrumental variable estimation. Also, the child's study habits proxied by school attendance, as expected, does well in improving educational attainment.

VI. CONCLUSION

This paper has gone further in discussing determinants of educational attainment arguing in support of the importance of making traditional school resources more available. Using data on

[13] These estimates are qualitatively similar to those gotten by Leóna & Valdivia (2015) who used a similar two-stage procedure and found that not accounting for school choice restrictions underestimates the effect of school resources by about a 100% in their Peruvian sample.

Burkinabe children, my empirical analysis indicates that failure to correct for school choice constraints related with the geographical inequalities in the distribution of useful school resources significantly understates the relevance of school resources for educational achievement. My findings suggest that school resources are also important in incentivising households to send girls to school. This is relevant because policy that make school resources more available in Burkina Faso will aid in reducing the gender gap in education, which stands at 15% (The World Bank, 2015).

It is important to note the context in which the results in this paper have been gotten. Burkina Faso has a weak educational institution with poor infrastructure and inadequate reach. Given the non-linear impact of school resources seen in the literature, conditions in Burkina Faso position it well to have high margins of benefit by improving the quality of its schools. This limits the applicability of my findings.

I have approached the question of the relevance of school resources for educational attainment by looking at easily observable school inputs; going a bit further to aggregate them into a single measure of quality to get a sense of how they together influence educational delivery. Nonetheless, other factors that are not easily observable but may be more relevant to academic performance, such as management practices and pedagogy, were not considered. The drawback of my methodology is that those observable school resources may be available but useless for learning if schools have poor management practices and inefficient pedagogy. In order words not putting school inputs to proper use. Accounting for management practices and pedagogy may make our models fit the data better. This should be the focus of research, seeking to answer similar questions, going forward.

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VIII. APPENDIX

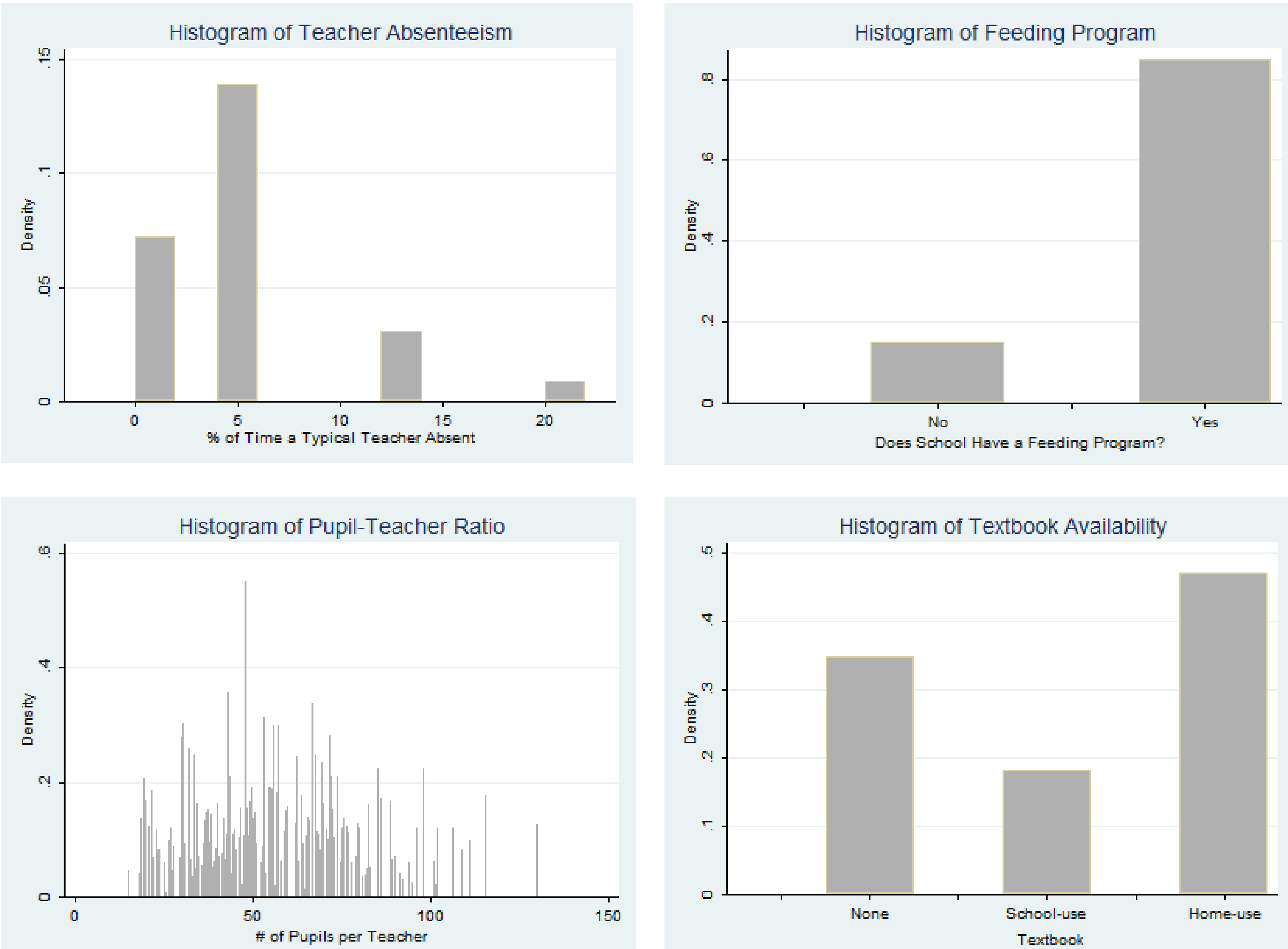
Table A.1: Descriptive Statistics of variables used in the regression analysis

Variable	Obs.	Mean	Std. Dev.	Min	Max
Mathematics	7456	.88	1.04	-.63	2.02
Language	7459	.84	1.15	-.56	2.63
Male	7465	.51	.50	0	1
Attendance	7394	4.9	.51	0	6
Highest Schooling HH	7465	5.5	1.26	2	6
HH Asset Index	7459	.14	1.66	-2.02	9.95
Pupil-Teacher Ratio	7465	55.06	22.33	15	130
Textbook Availability	7465	1.12	.90	0	2
Feeding Program	7465	.85	.35	0	1
Teacher Absenteeism	7465	5.30	4.40	1	20
Attends School Type 1	7465	.33	.47	0	1
Attends School Type 2	7465	.34	.47	0	1
Attends School Type 3	7465	.33	.47	0	1
# of Classrooms of School Type 1 in the Village	7465	1.12	1.92	0	9
# of Classrooms of School Type 1 in the Village	7465	1.45	2.38	0	12
# of Classrooms of School Type 1 in the Village	7465	1.10	1.63	0	9
Normalized Poverty Score	7465	3.04	1	-2.54	10.32

Table A.2: Principal Component Analysis – HH Asset Index

Variable	Coefficient
Floor material	
Natural Material (earth, sand, dung)	−.42
Rudimentary Material (wood planks, palm, bamboo)	.05
Finished Material (polished wood, vinyl, asphalt, ceramic, cement, carpet)	.42
Roof material	
Natural Material (no roof, stubble)	−.28
Rudimentary Material (rustic mat, palm, bamboo, wood planks)	.01
Finished Material (metal, wood, cement, shingles)	.40
Other asset ownership	
Radio	.26
Mobile phone	.26
Watch	.22
Bicycle	.20
Motorcycle	.31
Animal cart	.25
Cattle	.13
Percentage of overall variability explained by the first principal component	20.8

Fig. A.1: Distribution of Individual School Resources



Note: Teacher Absenteeism is seen as a discrete variable due to the questionnaire design, which has four options to choose from.

Fig. A.2: Alternative representation of the distribution of School Quality Index